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Human-Infrastructure System Assessment for Military Operations

Assessing Socioeconomic Impacts of Cascading Infrastructure Disruptions Using the Capability Approach

Yi (Victor) Wang, Armin Tabandeh, Paolo Gardoni,
Tina M. Hurt, Ellen R. Hartman, and Natalie R. Myers

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Abstract

U.S. Army doctrine requires that commanders understand, visualize, and describe the infrastructure component of the Joint Operating Environment to accomplish the Army's missions of protecting, restoring, and developing infrastructure. The functionality of modern cities relies heavily on interdependent infrastructure systems such as those for water, power, and transportation. Disruptions often propagate within and across physical infrastructure networks and result in catastrophic consequences. The reaction of communities to disasters may further transfer and aggravate the burden and facilitate cascading secondary disruptions. Hence, a holistic analysis framework that integrates infrastructure interdependencies and community behaviors is needed to evaluate vulnerability to disruptions and to assess the impact of a disaster. The research for Human-Infrastructure System Assessment (HISA) for Military Operations adopts the Capability Approach (CA) to measure and predict the impact of potential infrastructural interdictions on the City of Maiduguri, Borno State, Nigeria. With the CA, 10 capabilities are identified to describe the well-being levels of Maiduguri. To quantify these 10 capabilities, 16 indicators were chosen to represent them. These indicator justifications provide the rationale for choosing the indicators for the corresponding capabilities and predictive modeling. Developing probabilistic predictive models of the indicators (or their indices) allows analysis of social well-being in relationship to cascading infrastructure failure.

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Abbreviations

Term	Meaning
ASAALT	Assistant Secretary of the Army for Acquisition, Logistics, and Technology
BH	Boko Haram
CA	Capability Approach
CDC	Centers for Disease Control and Prevention (U.S.)
CERL	Construction Engineering Research Laboratory
CIA	Central Intelligence Agency (U.S.)
EFinA	Enhancing Financial Innovation and Access, Nigeria
ERDC	Engineering Research and Development Center
FAO	Food and Agriculture Organization of the United Nations
FME	Federal Ministry of Education of Nigeria
FMH	Federal Ministry of Health of Nigeria
FORM	First-Order Reliability Method
GDP	gross domestic product
GNI	gross national income
HDI	Human Development Index
HDR	Human Development Report
HISA	Human-Infrastructure System Assessment (for Military Operations)
IDP	internally displaced person
IPUMS	Integrated Public Use Microdata Series
JMP	Joint Monitoring Programme of the World Health Organization/United Nations Children's Emergency Fund
LGA	local government area
MCMC	Markov Chain Monte Carlo (simulation)
MPC	Minnesota Population Center
NBS	National Bureau of Statistics, Nigeria
NEPA	National Electric Power Authority (Nigeria)
OED	Oxford English Dictionary
PDF	probability density function
PROSAB	Promoting Sustainable Agriculture project in southern Borno State (Nigeria)
SMART	specific, measurable, attainable, relevant, and timely
SORM	Second-Order Reliability Method
UBE	Universal Basic Education (Nigeria)
UBEC	Universal Basic Education Commission (Nigeria)
UNDP	United Nations Development Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNGA	United Nations General Assembly

Term	Meaning
UNICEF	United Nations Children's Emergency Fund
UPE	Universal Primary Education, Nigeria
USACE	United States Army Corps of Engineers
WHO	World Health Organization

Preface

This study was conducted for the Assistant Secretary of the Army for Acquisition, Logistics, and Technology (ASAALT) under Project No. 405479, “Human Infrastructure System Assessment for Military Operations.” The technical monitor was Mr. Ritchie L. Rodebaugh of the U.S. Army Engineer Research and Development Center’s Geospatial Research Engineering Office of Technical Director (CEERD-TZ-T).

The work was performed by the Ecological Processes Branch (CNN) of the Installation Division (CN), U.S. Army Engineer Research and Development Center, Construction Engineering Research Laboratory (ERDC-CERL). At the time of publication, Dr. Chris C. Rewerts was Chief, CEERD-CNN; Ms. Michelle Hanson was Chief, CEERD-CN; and Mr. Ritchie L. Rodebaugh, was the Technical Director for Geospatial Research and Engineering (CEERD-TZ-T). The Deputy Director of ERDC-CERL was Dr. Kirankumar Topudurti, and the Director was Dr. Ilker Adiguzel.

COL Bryan Green was the Commander of ERDC, and Dr. Jeffery P. Holland was the Director.

1 Introduction

1.1 Background

Modern cities are comprised of complex infrastructure networks, such as those for power, water, and transportation, which interact with one another and jointly function to provide resources and services to city residents. As cities continue to expand and prosper, the ever-growing population imposes pressing challenges to the urban infrastructure systems in every aspect. Even for properly designed infrastructures that satisfy people's needs in normal-functioning scenarios, infrastructure performance is often vulnerable to unexpected disruptions due to factors such as natural disasters or hostile human activities. In such situations, the performance of the city and the well-being of the society can be significantly impacted, resulting in social disruptions related to economic loss, humanitarian crisis, and demographic loss.

Urban infrastructure failures are likely to stimulate strong reactions from the population. A direct consequence of most system failure is difficulty for residents to access life-supporting resources. For example, people may have to line up at gas stations to purchase overpriced fuel, travel a longer distance to access water, or turn to diesel generators when the power grid is disrupted.

In reality, infrastructure failure and community reactions are mutually dependent, which further complicates the problem. For example, people may have to travel through the transportation network to deliver or retrieve resources, while some infrastructural interdependencies are realized by delivering commodities from one facility to another via transportation. When congestion increases due to people's response to system failure, the fluidity of commodity flow may be compromised and the cascading effect could be further exacerbated. Therefore, instead of allowing only one-directional impacts from system failure to population response, the impacts of human activities on physical system performances should also be considered.

1.2 Human-Infrastructure Systems Assessment (HISA)

The HISA research project is sponsored by the U.S. Army Corps of Engineers – Engineer Research Development Center (USACE-ERDC). This research evaluates the effects of infrastructure disruptions on the well-being of civilian populations. Critical infrastructure systems (e.g., communication, electricity, food security, transportation, and water) provide vital services that support and enable societal functions. Consequently, their loss due to disasters, terrorism, population migrations, or military operations can potentially result in widespread, catastrophic disruptions. Of particular concern are the interdependencies between infrastructures—failures in one system can rapidly lead to failures in other systems, in a chain reaction that greatly exacerbates the situation. Given the physical placement and interconnections of the various components of the infrastructure networks, HISA performs three calculations:

- HISA estimates the cascading physical damage on infrastructure components (e.g. generators, storage tanks, and bridges)
- HISA translates that damage estimate into a change in available infrastructure services.
- HISA utilizes societal traits to compute changes in safety, health, shelter, and income.

For example, the failure of a critical water pump may shut down the power plant due to the need for cooling. This failure translates into a restricted loss of water services, but a widespread loss of electricity. The significance, or effect, of these failures is dependent on how communities use the services. Households unconnected to the electrical grid will not be impacted by electrical failure. On the other hand, commercial vendors dependent on the electrical grid to refrigerate food supplies could potentially affect regional health conditions. Utilizing societal traits enables agencies to plan for the potential effects of the loss of infrastructure services, focus efforts towards rehabilitation, and/or create additional services.

The goal of HISA is to build a model that represents combined human-infrastructure systems so that the potential impacts of infrastructure changes on social well-being in Army-relevant contexts can be explored. This model will be designed to provide possible policy insights into how best to protect crucial infrastructures, reserve emergency supplies, and avoid humanitarian disasters.

1.2.1 Maiduguri case study

Maiduguri is the capital city of Borno State in northeastern Nigeria ($11^{\circ}51'N$, $13^{\circ}05'E$), with an estimated total population of 1.2 million. Concurrent with rapid urban growth, the local government has been facing additional severe challenges. Challenges include natural hazards such as drought and floods that cause significant adverse effects (Odihi 1996), both active military events and terrorist attacks that threaten people's daily life and the security of urban infrastructure (Ibeh 2015), and large numbers of internally displaced persons (IDPs) fleeing into Maiduguri after terrorist attacks, which exhaust the resources in the city, resulting in further pressure on the system (Haruna 2015). From this angle, the model aims to better understand and interpret these pressing social concerns, providing possible policy insights into how best to protect crucial infrastructures, reserve emergency supplies, and avoid humanitarian disasters.

The HISA pilot study, Maiduguri, Nigeria, is a beta application of the HISA process for a 12-square-mile region in northeastern Nigeria that includes the municipal jurisdiction of Maiduguri. Maiduguri is located in the heart of the rebel activity of Boko Haram and experiences frequent attacks on its infrastructure. The Alau Reservoir is the primary source of water for Maiduguri residents. The shrinking of Lake Chad has also caused several conflicts to emerge as sources for water, food, and livelihoods disappear. The pilot study illustrates the value of the HISA capability and validates results by using scenarios that mimic past events.

1.3 Objective

The objective of this research is to develop and test a network interdependency model that provides quantitative geospatial representations of socioeconomic impacts of changes to or failures within an infrastructure system, while considering that population reactions to infrastructure failures may change demand patterns, which in turn, may affect the entire system.

1.4 Approach

This report provides a review of the reliability-based capability approach, discusses the proposed framework, discusses the selection of capabilities and their indicators and regressors, develops probabilistic predictive mod-

els of the indicators (or their indices), presents the requirements of the capability assessment, and presents an illustrative example that describes the proposed framework.

Significant work remained on operationalizing the reliability-based capability approach and transforming the methodology into practical tools. In particular, different steps of operationalizing the capability approach are explained through a case study example. Furthermore, probabilistic predictive models are developed for the selected capability indicators and then the models were calibrated using the observed data available for Maiduguri, Nigeria. The predictive models relate the capabilities of individuals to the three influencing resources (i.e., internal, external, and social and material structure of the society). The developed predictive models were used to formulate a system reliability problem. In the reliability problem, which combinations of indicator indices can lead to different capabilities states are explained. Specifically, this report illustrates how to define and estimate the probability of achieving different capabilities states that are in principle acceptable, tolerable, and intolerable. An important consideration in defining the thresholds between different capabilities states is human rights that specify the minimum moral thresholds that all individuals are entitled by virtue of their humanity. The final product, summarizing the results of the reliability analyses, is a series of maps that show the spatial distribution of each capability dimension over the given region as well as their aggregation.

1.5 Scope

Preceding technical reports on this subject include:

Hart, Steven D., J. Ledia Klosky, Scott Katalenich, Berndt Spittka, and Erik Wright. (2014). *Infrastructure and the Operational Art: A Handbook for Understanding, Visualizing, and Describing Infrastructure Systems.* ERDC/CERL TR-14-14. Champaign, IL: ERDC-CERL.

Myers, Natalie R., Angela M. Rhodes, Jeanne M. Roningen, Thomas A. Bozada, Lucy A. Whalley, Susan I. Enscore, Tina M. Hurt, David A. Krooks, Ghassan K. Al-Chaar, George W. Calfas, and Dawn A. Morrison. 2016. *Understanding the Effects of Infrastructure Changes on Sub-Populations.* ERDC TR-16-3. Champaign, IL: ERDC-CERL.

Xin Wang, Liqun Lu, , Zhaodong Wang, Yanfeng Ouyang, Jeanne Roningen, Scott Tweddle, Patrick Edwards, and Natalie Myers. 2016. *Assessing Socioeconomic Impacts of Cascading Infrastructure Disruptions in a Dynamic Human-Infrastructure Network.* ERDC TR-16-11. Champaign, IL: ERDC-CERL.

2 The Capability Approach to Societal Impact of Disruptions

In order to quantify the effects the infrastructural interdictions have on society and local populations of Maiduguri, the Capability Approach (CA) was adopted. The CA was pioneered by the Nobel prize-winning economist Amartya Sen and philosopher Martha Nussbaum (Murphy and Gardoni 2006, 1074; Nussbaum 2000; 2007; Robeyns 2006, 351; Sen 1989; 1999a). It has been widely used as the appropriate methodology to measure human development. Based on the CA, the United Nations Development Programme (UNDP) has, since 1990, annually published the Human Development Report (HDR) with Human Development Indices (HDIs) indicating the human development status of countries throughout the world (see e.g., UNDP 1990, 2000, 2010, 2015). Within the field of risk and hazard research, Dr. Paolo Gardoni and Dr. Colleen Murphy have further developed the CA and introduced it to risk and hazard impact analysis (see e.g., Gardoni and Murphy 2008, 2009, 2010, 2014; Murphy and Gardoni 2006, 2007, 2008, 2010a, 2010b, 2012a, 2012b).

The core concepts of the CA are an individual's functionings and capabilities. An individual's functionings are "what an individual does or becomes in [her or his] life that is of value" (Murphy and Gardoni 2006, 1074). Examples of functionings include "Being Physically Safe," "Being Sheltered," Being Mobile, and "Having Access to Medical Services." Meanwhile, capabilities are the "constitutive dimensions of individual well-being and reflect what individuals have a genuine opportunity to do" (Gardoni and Murphy 2014, 1210). The implementation of the CA can effectively capture the societal impacts that resulted from the infrastructural interdictions of interest. First, the CA avoids the narrow identification of easily-quantifiable consequences, such as fatalities, injuries, damaged structures, and direct economic losses. Second, the CA provides an accurate, uniform, and consistent metric for quantifying societal impacts. Third, the CA is based on an objective methodology, with transparent value judgments to determine the level of acceptable and tolerable risks instead of resorting to individuals' preferences (Murphy and Gardoni 2006, 1077-1080).

In the context of risk analysis, Drs. Murphy and Gardoni developed a capabilities-based risk analysis to quantify the consequences of hazardous scenarios. In this approach, the potential societal impact of disruptions is

evaluated in terms of individuals' capabilities as constitutive elements of well-being. The capabilities of individuals refer to their *genuine opportunity* to become or achieve things they have reason to value. Examples include being adequately nourished, having shelter, being mobile, and becoming educated. Such doings and beings are called functionings. The capabilities of individuals are influenced by:

- their internal resources,
- their external resources, and
- the social and material structure of the society within which they act.

Internal resources refer to personal skills, talents, and psychological well-being. Examples of external resources include income and wealth. Customs and traditions, laws, physical infrastructures, and language are all examples of the social and material structures that are salient for determining the capabilities.

In order to implement the CA, two steps needed to be taken. The first step is to identify the appropriate capabilities (e.g., Figure 1, Figure 2, and Figure 3), and the second step is to select the pertinent indicators to represent these capabilities. The first step required the researchers to follow three criteria, as listed below (Gardon and Murphy 2010, 623):

- The selected capabilities need to be relevant and important.
- The minimum number of possible capabilities needs to be specified.
- Each of the selected capabilities needs to provide information that cannot be ascertained from the other capabilities.

The CA process is accomplished by the steps listed below:

- **Selection of capabilities.** Identify capabilities that provide an accurate picture of the societal impacts.
- **Selection of indicators.** Pick appropriate indicators that track the societal impacts on the capabilities of interest.
- **Scaling indicators.** Scale the salient capability indicators to generate the corresponding capability indicator indices.
- **Development of predictive models for indicator indices.** Develop regression models that can effectively forecast the changes in the values of capability indicator indices due to societal impacts of disruptions to civil infrastructure.

- **Development of an aggregated measure of capabilities.** Develop composite measure that summarizes the changes in capability indicator indices due to disruptions to civil infrastructure.

Figure 1. Capability of accessing potable water (source:: Water Scarcity, Daily Post Nigeria, Ugwuanyi, 20 January 2015).



Figure 2. Capability of being mobile (source: Bella Africana.com).



Figure 3. Capability of having access to electricity (source: www.news24.com).



2.1 Selecting capabilities

Through the combination of literature review, examination of quantitative datasets, and development and qualitative analysis of the Specific, Measurable, Attainable, Relevant, and Timely (SMART) documents (to be published by ERDC-CERL in 2017), the first step was to identify the 10 capabilities in our study. According to the capabilities identified, 16 indicators were selected from two Nigerian surveys to represent the 10 capabilities. In order to test, as well as enhance, this process of indicator selection, an extensive literature review was conducted, along the corresponding capability dimensions. This extensive literature review provides the rationale for final selection of the 16 capability indicators.

Following these criteria, 10 capabilities were selected, based on scholarly literature review, the development of SMART documents, and rounds of pertinent academic discussions. The 10 capabilities are:

1. “Meeting the Physiological Needs,”
2. “Being Physically Safe,”
3. “Being Sheltered,”
4. “Having Access to Energy,”
5. “Earning Income,”
6. “Owning Property,”
7. “Being Mobile,”

8. “Being Educated,”
9. “Having Access to Medical Services,” and
10. “Being Socially Connected.”

The selection of capabilities was initiated and promoted through a combination of three processes:

- brainstorming guided by the existing literature on human well-being and capability,
- examining the availability of data that represent human capabilities, and
- developing and qualitatively analyzing the SMART documents.

Brainstorming generated a list of 49 aspects of human well-being and capabilities such as values, language, religion or faith, gender roles, ethnic difference, risk-taking tendency, disaster preparedness, public health, and education. Researchers referenced the literature of capability studies (e.g., Knight 1989; Nussbaum 2007; Oxenham et al. 1989; Wolff and de-Shalit 2007), and then reformulated the pertinent conceptual categories to reflect the capability dimensions. The academic explorations into and discussions on the capability conceptualization were later condensed within a matrix of capabilities (Table 1) that distinguished the ten identified capabilities from the potential regressors for the regression model used for this work.

Researchers then scrutinized the existing quantitative datasets that were used to reflect the human capabilities in the communities of Maiduguri, Nigeria. The datasets examined included Nigeria’s National Core Welfare Indicators Survey (NBS [National Bureau of Statistics, Nigeria] 2006), the Harmonised Nigeria Living Standards Survey (NBS 2009), and the datasets covering Nigeria from the website of Integrated Public Use Micro-data Series, International (IPUMS International) and (MPC [Minnesota Population Center] 2016). Attention was given to what variables are applied, and to what extent the variables are applied to represent the capability dimensions that were identified and conceptualized.

During examination of the quantitative datasets, researchers noticed that these datasets have three limitations, as listed below:

- There is a lack of highly pertinent variables of interest, such as crime rate in a community to manifest the capability of “Being Physically Safe” and the annual household income to reflect the capability of “Earning Income.”
- A number of highly relevant variables of interest are present in separate datasets, while the regression model used here requires them to be in one single dataset.
- The data collected within the datasets were examined, but they had a relatively coarse granularity, as the database of IPUMS International only has data at the nation-state level, and the two Nigerian surveys have data at a maximum of local government area (LGA) level, which is lacking neighborhood, community, or household level of information.

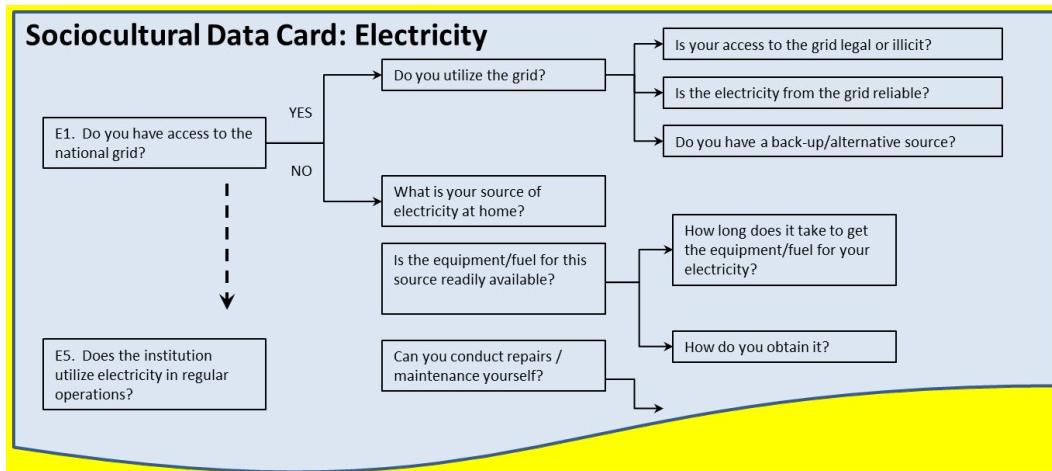
Despite these limitations, examination of the dataset confirmed that conceptualization of capability dimensions through developing a matrix of capabilities is meaningful and can be operationalized.

ERDC-CERL (Construction Engineering Research Laboratory) then developed the SMART documents in the format of questionnaires to gain insight into the societal characteristics of communities (Figure 4 illustrates the data question sequence format). The SMART documents were designed to characterize five layers of infrastructure (i.e., communication, electricity, food security, transportation, and water). Through analysis, researchers confirmed strong connections between the major themes of the SMART documents and the capability dimensions conceptualized within the matrix of capabilities (see Table 1).

Assessing infrastructure’s impact with SMART documents follows the general sequence shown in Figure 4, and allows for:

- **Defined Socio-Cultural Data Needs** – understand how society uses infrastructure and the impact of disruptions.
- **Standardized Data** – standardized responses support an area-wide understanding of the human-infrastructure environment.
- **Data Guides** – guides analysts in interpreting and understanding data.
- **Field Guides** – instructions for observers and data collectors.
- **Shareable Reports & Dashboards** – visualization tools to display and communicate data and assessments.

Figure 4. Data question collection sequence.



2.2 Selecting indicators and regressors

The second step of implementing the CA was selecting the pertinent indicators representing the appropriate capabilities. This process required the researchers to meet two criteria. The selected indicator needed to be representative of the corresponding capability and the chosen indicator needed to be intuitively plausible (Gardoni and Murphy 2010, 624–626). In order to ensure the representativity and plausibility of the indicators reflecting the appropriate capabilities, 16 indicator justifications were developed with respect to each of the selected 16 capability indicators. These 16 capability indicators correspond to the 10 capabilities that were identified (see Table 1). Theoretically, an indicator is a “statistic of direct normative interest which facilitates concise, comprehensive and balanced judgments about the condition of major aspects of a society” (Land 1975, 15). A good indicator needs to have high construct validity, or “the degree to which a measure of a concept actually reflects the concept” (Stinchcombe and Wendt 1975, 58). The indicators selected to reflect the capability dimensions need to be unidimensional, occupying a single causal locus in the corresponding theoretical domain (Stinchcombe and Wendt 1975, 60). In addition, the indicators need to have good reliability, which refers to the quality of being replicable when used at different times (Stinchcombe and Wendt 1975, 60).

Based on the 10 capabilities identified and conceptualized, the 16 indicators represent and measure the capabilities. These indicators differ from the regressors. A regressor is a variable from a quantitative dataset used and determined by the regression model as being pertinent to predicting

the value of a capability indicator of interest. Within the study, both indicators and regressors are based on the variables from the quantitative datasets that were investigated. Each indicator provides a schematic of the capability dimension it represents, and each can be derived from the variables from the same quantitative dataset to which the indicator belongs. Any variable that is not the indicator within the dataset becomes a potential regressor for the regression model to determine. Once examined by the regression model, a potential regressor will be either discarded from the model or contained as a regressor for deriving the capability indicator.

Based on these understandings, the appropriate indicators representing capability dimensions were identified from the two Nigerian surveys (NBS 2006; 2009), since these surveys provide the finest granularity among the datasets available. Concurrently, existing literature was referenced for evidence to support or disagree with the rationale for selecting capability indicators. This literature evidence is also reflected within Appendix A of this report, “Capability and Indicator Descriptions.” Bounded within the theoretical framework delineated by the reviewed literature, 16 indicators were selected from the two Nigerian surveys to represent the 10 identified capabilities (Table 1). These indicators were selected based on relevancy and the availability of data.

Table 1. Matrix of the 10 capabilities and the 16 supporting indicators.

Capability	Indicator
Meeting physiological needs	Main source of drinking water
	Frequency of problems with supply of drinking water
	Frequency of problems satisfying food needs
Being physically safe	Do members feel safe walking on the street at night?
Being sheltered	Frequency of problems paying house rent
Having access to energy	Source of electricity
	Number of hours without electricity in previous 24 hours
Earning income	Household financial situation
Owning property	Number of household durables
	Dwelling ownership
Being mobile	Time to nearest food market
Being educated	Time to nearest primary school
	Frequency of problems paying school fees

Capability	Indicator
Having access to medical services	Time to nearest hospital
	Frequency of problems paying for healthcare
Being socially connected	Can household depend on religious association during difficult period?

2.3 Review of the capability identification and indicator selection process

Based on the capability identification and indicator selection with the CA, a corresponding model was developed that measures the pre-interdiction capability level of the study area, and a logistic regression model was developed that provides the prediction of the post-interdiction capability level of the study area—Maiduguri, Nigeria. Through comparing the pre-interdiction and post-interdiction capability levels of the study area, the effects to the society and local populations resulting from the infrastructural interdictions of interest were successfully quantified.

The 16 capability indicator justifications provide the rationale for the decisions of selecting the pertinent indicators to represent the corresponding 10 capabilities. For each indicator, researchers present the capability that the indicator represents, display the survey question and the corresponding answers for deriving the values of the indicator, detail the pertinent information, elaborate on the logic for choosing the indicator, and identify whether the indicator is replicable.

The societal impact is obtained by predicting the individual capability level as influenced by the physical damage, its cascading effects, and the propensity of the society impact (i.e., the social vulnerability), which is influenced by its socioeconomic characteristics.

Including the population into this analysis embraces the challenges of representing the community and the day-to-day life of individuals within that community. The analysis looks at indicators and regressors that affect a given individual's capability. The 10 capabilities analyze the well-being of society. Each capability has an indicator or multiple indicators, based on the determining factors, to identify the capability and the availability of data to substantiate the determination.

Tabandeh et al. (2016) extended the capabilities-based risk analysis to predict the capabilities of individuals by using a system reliability approach. The overall capability of individuals is treated as a system of interconnected components. Indicator indices, as proxies of specific capabilities, are the components of the system. To determine the overall capability of individuals, both the values of indicator indices and how those values collectively determine the overall capability must be known. It is proposed to develop empirical probabilistic predictive models for each indicator index that relates the values of the indicator indices to a set of influencing factors. The developed probabilistic models, along with the configuration of indicator indices in the system, can be used to formulate a system reliability problem and predict the capabilities of individuals, for example, in the aftermath of a disruption. Comparing the predicted values in the post-disruption condition with those measured/predicted in the pre-disruption situation can give an estimate of the extent of the societal impact.

Concurrent with the growth of urban population and the increased rate of development, the susceptibility of human communities to potentially devastating consequences of hazards is increasing. Consequences of past disasters have shown that such events can adversely impact people and communities in which they live and result in significant loss of lives, business interruption, direct and indirect economic loss, and various other societal impacts. Examples of such disasters over the past decade include 2005 Hurricane Katrina in the United States, 2008 Sichuan earthquake in China, and 2011 Tohoku earthquake and tsunami in Japan. The consequences of such events can simply go beyond the geographic boundaries of the region that has been physically impacted. Also, the impact could be at multiple scales affecting governments, institutions, economic sectors, livelihoods, and people. These past events have highlighted the significance of accounting for the far-reaching societal impacts, which is crucial both for the pre-event effective mitigation planning and the post-event optimal resource allocation.

Similar hazards in different communities can result in dramatically different consequences. Furthermore, it is increasingly becoming clear that people and groups are impacted, react, adjust, and recover in different ways when a disruption occurs. Such differences are rooted in the societal characteristics of the communities. The ultimate impact of disruptive events is the product of dynamic interactions between the built environment (e.g., civil infrastructures) and the societal characteristics of the community.

Due to the interdependencies of the infrastructure networks, the damage to the components of each network can propagate through different layers and result in cascading failures. The damage to the urban infrastructure would stimulate strong reactions from the population. The extent of such reactions and the subsequent chaos is related to the level of the realized damage and the societal characteristics of the communities. The important challenges in assessing the societal impact are to:

- determine what consequences are contributing and should be considered,
- develop a mathematical formulation to quantify the overall consequences both in the immediate aftermath of the disruption and over time, and
- define the acceptable and tolerable levels of the perceived consequences.

The particular focus is to quantify the societal impact of disruptions to civil infrastructure systems. To this end, researchers identified the dimensions of well-being which are the testbed in order to quantify, compare, and aggregate the ultimate impact of various disruptive events.

3 Extending the Capability Approach for Predictive Analysis

3.1 Reliability-based capability approach

The reliability-based capability approach augments the indicators and capabilities by scaling the indicators to create indicator indices, developing probabilistic predictive models of the indicator indices, and developing an aggregate measure of the indicator indices. Here, the theoretical background and the requirements of each step are briefly explained.

In selecting the capabilities, the main focus is on the underlying values of the problem, based on which capabilities might become important and the others trivial (capabilities relevance/significance). Among the set of all pertinent and significant capabilities, the particular interest is to select the smallest subset of capabilities that can provide all the required information (i.e., cover all the important dimensions of well-being in relation to the problem under study). This property is called the capability parsimony. Furthermore, it is desirable that each of the selected capabilities provides information that cannot be ascertained from the other ones. This property is called the capabilities orthogonality. The orthogonality property demands to avoid redundant information (i.e., selecting similar capabilities) that leads to overemphasizing a subset of well-being dimensions in a sense causing double counting.

Because capabilities are not directly measurable, indicators are selected as proxies for each capability. More precisely, the indicators are quantifying the achieved functionings. Hence, the selected indicators should be representative of the corresponding capability. Furthermore, the availability of data is an integral part of selecting the indicators. Typically, an ideal list of indicators is initially developed and justified using the best of knowledge available in the literature that is also supported by personal explanations. The ideal list might then be tailored/adjusted based upon the availability of data. The ideal list, however, could still be used as a guidance of the future work to collect the required data.

3.1.1 Scaling indicators

Before developing the aggregate measure, the indicators are scaled to create the indicator indices as follows in Equation (1):

$$II_j := \frac{I_j - I_{\min}}{I_{\max} - I_{\min}}, \quad (1)$$

where II_j is the indicator index j that varies in the range from 0 (minimum achievement) to 1 (maximum achievement); I_j is the achievement in indicator j ; I_{\min} , and I_{\max} are the boundaries that specify the absolute minimum and maximum values of indicator j . The scaling of the indicators makes them dimensionless and provides a common ground to compare and aggregate indicators with different units and different ranges of variation.

3.1.2 Indicator predictive models

In this step, probabilistic predictive models are developed for the indicator indices. There is a two-fold objective in developing the probabilistic predictive models: (1) relating the values of the indicator indices to their influencing factors, including individuals' personal resources, wealth, social and material structure of the community within which individuals are acting, like the status of civil infrastructures (e.g., transportation network, water distribution network, or power grid), and (2) accounting for the prevailing sources of uncertainty in quantifying the indicator indices; specifically, when predicting the values of the indicator indices in the future, it is important to acknowledge the presence of uncertainties and appropriately treat them (for discussions on the different sources of uncertainty, see, for example, Murphy, Gardoni, and Harris Jr. 2011). The models are calibrated by using the observed data. In some cases, the observed data might also be supported by subjective information. The calibrated models can then be used, in the context of risk analysis, to predict the new values of indicator indices when the influencing factors change due to the impact of a disruption. It is worth noting that the sequence of scaling the indicators to develop indices and developing predictive models might change. For example, in the case of categorical indicators, researchers might first develop the predictive model of the indicator and then scale the indicator to create the index.

3.1.3 Aggregate indicators

The last step is to aggregate the indicator indices and determine the overall capabilities of the units of study (e.g., individuals, households, communities, countries). Depending on the values of the indicator indices and

their combination, the capabilities state of each unit is one of the following:

- acceptable
- tolerable
- intolerable

A system reliability problem can be formulated and analyzed to determine the capabilities state of each unit, accounting for the uncertainties in the values/categories of the indicator indices. The first step in the system reliability formulation is to define the states of the indicator indices (i.e., a map from the values/categories of the indicator indices to a set of predefined states). The second step is to describe what combinations of the indicator indices, in terms of their states, give rise to each of the three capabilities states. In the last step, a reliability analysis is performed for each unit, using the developed combination schemes and the probabilistic models of the indicator indices. The result of the reliability analysis for each unit is the probability distribution of its capabilities states.

3.2 Methods for predictive model framework

This section explains the proposed probabilistic formulation of indicator indices and how a Bayesian approach calibrates the models, using both the objective and the subjective information. The objective information refers to the observed data, and the subjective information refers to the experts' knowledge. Finally, an explanation is given about how to formulate the reliability problem and develop an aggregate measure of the indicator indices that summarizes the overall impact.

3.2.1 Formulation of the probabilistic predictive models

An empirical probabilistic models were developed to predict the values/categories of the indicator indices as functions of their influencing factors. The general form of the proposed probabilistic predictive models is as follows in Equation (2):

$$g\left[II_l(\mathbf{x}_l, \boldsymbol{\Theta}_l) \right] = \sum_{j=1}^{n_l} \theta_j x_j + \sigma_l \varepsilon_l, \quad (2)$$

where $g[\Pi_l(\mathbf{x}_l, \Theta_l)] := \ln\{\Pi_l(\mathbf{x}_l, \Theta_l)/[1 - \Pi_l(\mathbf{x}_l, \Theta_l)]\}$; $\Pi_l(\mathbf{x}_l, \Theta_l)$ is the predicted value of the l^{th} indicator index; $\mathbf{x}_l := (x_{l1}, \dots, x_{ln_l})$ is the set of regressors (i.e., influencing factors); $\Theta_l := (\boldsymbol{\theta}_l, \sigma_l)$ is the set of unknown model parameters that should be estimated, in which $\boldsymbol{\theta}_l := (\theta_{l1}, \dots, \theta_{ln_l})$; and $\sigma_l \varepsilon_l$ is the model error term, in which σ_l is the standard deviation of the model error and is assumed to be independent of \mathbf{x}_l (homoscedasticity assumption) and ε_l is a standard normal random variable (normality assumption). The accuracy of the model prediction depends on different factors, including the form of the model, the quality of regressors in a sense that having strong relation with the corresponding indicator index, and the size of the database used for model calibration (i.e., estimating Θ_l).

The predictive model in Equation (2) works well for integer- or real-valued indicators and, thus, their indices. However, in practice, there are indicators that are categorical and take values only from a finite set. For such indicators, the predictive model in Equation (2) does not apply; hence, multinomial logit model was developed to predict the outcomes of the categorical indicators. The general form of the model is as follows Equation (3):

$$\mathbf{P}[I_l(\mathbf{x}_l, \Theta_l) = k] = \begin{cases} \frac{\exp\left(\sum_{j=1}^{n_l} \theta_{lkj} x_{lj}\right)}{1 + \sum_{k=1}^{K_l-1} \exp\left(\sum_{j=1}^{n_l} \theta_{lkj} x_{lj}\right)}, & k \in \{1, \dots, K_l - 1\}, \\ \frac{1}{1 + \sum_{k=1}^{K_l-1} \exp\left(\sum_{j=1}^{n_l} \theta_{lkj} x_{lj}\right)}, & k \in \{K_l\}, \end{cases} \quad (3)$$

where $\mathbf{P}[I_l(\mathbf{x}_l, \Theta_l) = k]$ is the probability that the indicator l , $I_l(\mathbf{x}_l, \Theta_l)$, has the label $k \in \{1, \dots, K_l\}$; $\mathbf{x}_l := (x_{l1}, \dots, x_{ln_l})$ is a set of regressors; and $\Theta_l := (\boldsymbol{\theta}_{l1}, \dots, \boldsymbol{\theta}_{lK_l-1})$ is the set of unknown model parameters that should be estimated, in which $\boldsymbol{\theta}_{lk} := (\theta_{lk1}, \dots, \theta_{lkn_l})$. It is useful to note that $\{1, \dots, K_l\}$ is an ordered set where the assigned numbers (i.e., $k \in \{1, \dots, K_l\}$) are simply labels and do not show the actual gap between different k 's. Indices (i.e., $\Pi_l(\mathbf{x}_l, \Theta_l)$) can then be created by mapping the predicted indicators into numbers in the interval [0,1].

3.1.1 Bayesian updating and model selection

To estimate the unknown model parameters in Equations (2) and (3), a Bayesian updating rule (Box and Tiao 2011) was used, as follows in Equation (4):

$$f(\Theta_l) := \kappa L(\Theta_l) p(\Theta_l), \quad (4)$$

where $f(\Theta_l)$ is the posterior probability density function (PDF), representing the updated information about Θ_l ; $L(\Theta_l)$ is the likelihood function that contains the objective information about Θ_l , gained from the observed values of indicator (indices) and the regressors; $p(\Theta_l)$ is the prior PDF of Θ_l , representing the previous information about Θ_l , based on, for example, a similar past experiment or experts knowledge; and $\kappa := [\int L(\Theta_l) p(\Theta_l) d\Theta_l]^{-1}$ is a normalizing constant. A significant challenge in the Bayesian inference is computing κ . Typically, the integral $\int L(\Theta_l) p(\Theta_l) d\Theta_l$ is not analytically tractable, and its exact calculation is not feasible; however, the Monte Carlo simulation methods can be used (e.g., Gelman et al. 2014) to make approximate inference. Specifically, the Markov chain Monte Carlo (MCMC) simulation method (Haario et al. 2006) was used to estimate the posterior statistics of the unknown model parameters.

The likelihood function is proportional to the conditional probability of the observed indicator (indices) given a value of Θ_l . Because the predictive models for the integer-/real-valued indicators (see Equation (2)) and the categorical indicators (see, Equation (3)) are different, their likelihood functions would be different as well. Specifically, the likelihood function of the model in Equation (2) can be written as Equation (5):

$$L(\Theta_l) \propto \prod_{i=1}^n \frac{1}{\sigma_i} \phi \left[\frac{r_{li}(\Theta_l)}{\sigma_i} \right], \quad (5)$$

where $r_{li} := g(H_{li}) - \sum_{j=1}^{n_l} \theta_{lj} x_{lji}$ is the prediction's residual for the i^{th} observation (e.g., individual or household). Likewise, the likelihood function of the model in Equation (3) can be written as Equation (6):

$$L(\Theta_l) \propto \prod_{i=1}^n \prod_{k=1}^{K_l} P[I_l(x_{li}, \Theta_l) = k]^{1_{\{I_{li}=k\}}}, \quad (6)$$

where x_{li} and I_{li} are the regressors and the label of the indicator I_l for the i^{th} observation; $1_{\{I_{li}=k\}}$ is an indicator function and defined such that $1_{\{I_{li}=k\}} = 1$ when $I_{li} = k$ and $1_{\{I_{li}=k\}} = 0$, otherwise.

If there is no prior information, a noninformative prior PDF can be used such that it has no or minimal influence on the posterior PDF. Hence, the Bayesian inference is unaffected by information external to the observations. However, in practice, there might be external information beyond that provided by the observed data. For instance, in the case of a similar past experiment, the estimated posterior PDF could be used in that experiment as a prior PDF in the current calibration. Likewise, the expert knowledge could be incorporated to create a subjective prior PDF.

In general, it is possible to use more than just one database for calibrating the predictive models. In this way, both the number of observations (i.e., n in Equations (5) and (6)) and the number of variables (i.e., candidate x 's in Equations (2) and (3)) can be extended. Enriching the database has several advantages, including that it: (1) increases the possibility to find variables analogous to the ideal indicators; (2) increases the flexibility in selecting informative regressors that can sufficiently describe the variability in the corresponding indicators (i.e., increases the model accuracy); and (3) reduces the statistical uncertainty arises from the scarcity of data (i.e., the sampled data would sufficiently represent the actual situation of the population). However, in practice, there are difficulties to using such potentials. Typically, different databases do not have similar variables or observations; hence, the databases cannot simply be merged to create a larger database. Furthermore, the resolution of different databases might not be the same. There might be databases that give information at the individual level, whereas others might only provide a summary of the statistics at the local community level. If the same set of variables (i.e., I_j 's and x 's) are available in different databases, collected at different resolution or time periods, the updating rule of the Bayesian statistics will benefit in the following ways. First, the predictive models are calibrated, using one of the available databases to write $L(\Theta_l)$ along with a noninformative $p(\Theta_l)$ and estimate $f(\Theta_l)$. Next, the calibration process is repeated with a new set of

observations, but this time, with an informative $p(\Theta_i)$ that is the estimated posterior distribution from the previous run. This process can be repeated sequentially until all available databases are used.

Model selection is an integral part of developing the predictive models. First a pool of candidate regressors is created. Similar to the selection of the indicators, a list of ideal candidate regressors is developed that are believed to have impacts on the corresponding indicators. The ideal list includes different resources and constraints, listed earlier, that can influence the capabilities of individuals and, thus, the corresponding indicators. The ideal list might then be tailored based on the availability of the data. For practical prediction purposes, it is important to select regressors that are easily measurable/predictable at different locations and over time (e.g., over the region of interest in the aftermath of a disruption). Furthermore, it is desirable to eliminate the regressors that are not statistically significant in predicting the indicator (indices). For this purpose, a stepwise deletion process was used to successively eliminate one regressor, x_{ij} , at a time, based on the posterior statistics of the coefficient, θ_{ij} . After each elimination, the model is recalibrated with the remaining regressors. The process is recursive up to the point that the elimination of one more regressor leads to a relatively significant increase in σ_j in Equation (2) or a measure of the model error in Equation (3). The decision about the significance of the increase in the model error or where to stop the process is subjective, and it depends on the desired level of accuracy and the number of regressors left in the model.

The predictive models in Equations (2) and (3) are typically calibrated by using the data representing a stabilized situation of the society. When these models are used to predict the values/categories of the indicator indices in a chaos situation (e.g., in the aftermath of a disruption), care should be taken about changing the values of the regressors. To explain this point, attention is drawn to the relation between the indicator indices and their regressors. This relation can be of two kinds: (1) causal relation, in which a regressor is a sufficient cause to realize the indicator index, and (2) noncausal relation, in which there is only a pattern between the measured/predicted regressor and the corresponding indicator index. When the relation is causal, a change in the value of the regressor means a change in the value/category of the indicator index, both in the stabilized and the chaos situations. However, in the case of the noncausal relation, a change

in the value of the regressor happens in a condition different from the calibration one, and such a change can lead to a change in the value/category of the indicator (index) that might not replicate the reality. Hence, in this case, it might be reasonable not to change the values of such regressors.

3.2.2 Formulation of the reliability problem

The three capability states are defined in terms of the states of the indicator indices and their combinations. Murphy and Gardoni (2008) defined three states for the indicator indices with the same labeling as the capability states (i.e., acceptable, tolerable, intolerable). The principles of human rights (e.g., dignity, fairness, equality, and autonomy) can guide the description of what conditions constitute each of the acceptable, tolerable, and intolerable states of the indicator indices. Human rights represent moral standards that individuals in a society should not fall below (e.g., human right to life, health, and subsistence; Caney 2010). According to Murphy and Gardoni (2008), the values/categories of the indicator indices that correspond to the intolerable state are so low that no individual should ever experience that state, regardless of its duration. To determine the states of the indicator indices, with reference to the previous discussion, first partition the values/categories of each indicator index into its acceptable, tolerable, and intolerable states. This partitioning can be used to determine the state of indicator indices and eventually, the capabilities states in the immediate aftermath of a disruption. To determine the state of the indicator indices and, thus, capabilities states over time, the effect of recovery is accounted for. For example, the tolerable state of the indicator indices would become intolerable if the required recovery time to improve to the acceptable state exceeds a reference duration.

Mathematically, the indicator indices are modeled as discrete random variables with three possible states. The probability of each state can be written as Equation (7):

$$\begin{cases} \mathbf{P}(\mathcal{I}_j = \text{Acceptable}) = \mathbf{P}(II_j \geq ii_{j,\text{acc}}), \\ \mathbf{P}(\mathcal{I}_j = \text{Tolerable}) = \mathbf{P}(II_j < ii_{j,\text{acc}}, II_j \geq ii_{j,\text{tol}}, T_{R,j} \leq t_{R,j}), \\ \mathbf{P}(\mathcal{I}_j = \text{Intolerable}) = \mathbf{P}(II_j < ii_{j,\text{tol}} \cup \{II_j < ii_{j,\text{acc}}, II_j \geq ii_{j,\text{tol}}, T_{R,j} > t_{R,j}\}), \end{cases} \quad (7)$$

where $\mathcal{I}_j : [0,1] \times \mathbf{R}_+ \rightarrow \{\text{Acceptable}, \text{Tolerable}, \text{Intolerable}\}$ is the mapping function from the values of the indicator indices and the recovery time to their states; II_j is the random indicator index j modeled by Equation (2) or (3); $ii_{j,\text{acc}} \in (0,1)$ is the acceptable threshold that delimits the acceptable and tolerable states of the indicator index j ; $ii_{j,\text{tol}} \in (0, ii_{j,\text{acc}})$ is the tolerable threshold that delimits the tolerable and intolerable states of the indicator index j ; $T_{R,j}$ is the random recovery time to improve the state of the indicator index j from the tolerable state to the acceptable one; and $t_{R,j}$ is the reference recovery duration beyond which the tolerable state transforms into the intolerable one. It is useful to note that not all the indicator indices necessarily realize all the three states. There might be indicator indices for which only two states are defined (e.g., acceptable and intolerable).

The indicator indices can be viewed as the components of a system that are interacting with each other to satisfy a desired objective which in this case is the well-being of individuals. A fault-tree analysis is used to explore the conditions that can cause an unfavorable state of the system (i.e., tolerable or intolerable capabilities state). A fault tree is a deductive technique which starts with the unfavorable state of the system, called the top event, and then considers what can cause the occurrence of this state. The immediate causal events are identified and connected to the top event through a logic gate (i.e., an OR-gate or AND-gate). This deductive process then continues from each of the immediate causal events until a certain level of detail is reached, called the basic events. A fault tree schematically illustrates how the occurrence of the basic events collectively give rise to the top event. A collection of the basic events, whose joint occurrence ensures realizing the top event, is called a cut-set. A cut-set is said to be minimal if there is no redundant basic event in the collection. In other words, a minimal cut-set is no longer a cut-set if any of the basic events is removed from the collection. The occurrence of at least one minimal cut-set is sufficient to realize the top event. Subsequently, the probability of the top event comes down to the calculation of the probability of occurrence of at least one minimal cut-set from all the potential ones.

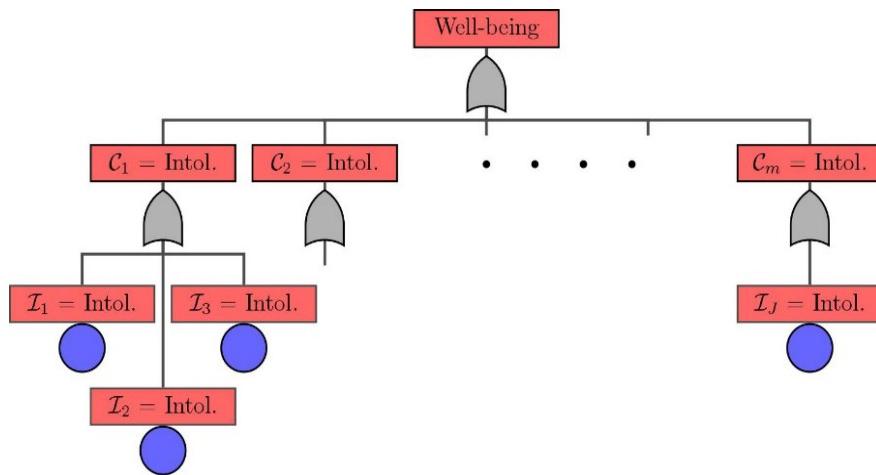
Figure 5 shows an example fault-tree where the top event is the intolerable state of the capabilities. The immediate causal events, $C_{1,\text{intol}}, C_{2,\text{intol}}, \dots, C_{m,\text{intol}}$ are the intolerable states of each capability, connected to the top event through an OR-gate. This structure implies that the top event occurs when at least one capability is in its intolerable state. The justification is that be-

cause capabilities are selected to be equally important and capture different aspects of well-being, failing to satisfy the acceptable state in each dimension leads to the unacceptable state (i.e., intolerable state in this example) of the entire system. In the next step, the intolerable state of each capability is determined in terms of the corresponding indicator indices. For instance, the causal event $C_{1,\text{intol}}$ occurs when at least one of the indicator indices I_1 , I_2 , or I_3 is in its intolerable state. Assuming a similar situation for all the other capabilities, the overall capabilities can be modeled as a series system of I_j 's, such that the intolerable state of any I_j leads to the intolerable state of the overall capabilities. Accordingly, the probability of the top event can be written as Equation (8):

$$\mathbf{P}(\mathcal{C} = \text{Intolerable}) = \mathbf{P}\left[\bigcup_{j=1}^J (\mathcal{I}_j = \text{Intolerable})\right], \quad (8)$$

where $\mathcal{C} : \{\mathcal{I}_1 \times \dots \times \mathcal{I}_J\} \rightarrow \{\text{Acceptable}, \text{Tolerable}, \text{Intolerable}\}$ is a mapping function from the states of the indicator indices to the capabilities state. For the purposes of calculation, reliability methods can be used to solve Equation (8). Examples of such methods include the First-Order Reliability Method (FORM), the Second-Order Reliability Method (SORM), or different simulation methods.

Figure 5. A fault-tree analysis of the intolerable state of a series system of capability indicators (University of Illinois).



3.3 Aggregation process

To evaluate the capabilities of individuals, first the states of each indicator are determined. Fault-trees are created that explain the topology of the system. Subsequently, for each community, system reliability problems are formulated, and the probability distribution of the states of each capability are calculated as well as the probability distribution of the overall capability states.

Figures C1 through C10 (see Appendix C) show the relation between the categories/values of the capability indicators and their states. The color-codes of the acceptable, tolerable, and intolerable states of indicators are green, yellow, and red, respectively. For a subset of indicators, only two states may be defined. Examples include the indicators “Main Source of Drinking Water” and “Source of Electricity.” For the indicator “Main Source of Drinking Water,” there are three possible categories; however, because the first two categories are not significantly different, it was decided to label both as an acceptable state and to label the last category as a tolerable state. For the indicator “Source of Electricity,” however, there are only two possible categories defined; hence, having defined two states, instead of three, is due to the constraint of the possible categories.

Using the probabilistic predictive models developed in the previous section, three-state random variables can be created, representing the three states of indicators. Figure 6 and Figure 7 show the fault-tree developed for the tolerable and intolerable states, which represent the relation between the states of the indicators and capabilities. Using the topology in the fault-tree, the probability distribution of the states of each capability as well as the overall capabilities can be calculated.

To illustrate the proposed formulation, system reliability analyses were performed for a household randomly selected from the database. The diagrams in Figure 6 and Figure 7 show the capability fault-tree analyses for pre- and post-disruption situations of the selected household. To create the diagrams, the probability distributions of each indicator was first obtained by using the developed probabilistic predictive models along with the definitions of the state based on the values/categories. In the next step, the developed formulation of the system reliability problem for each capability was used to obtain the corresponding probability distribution of the states. Finally, the expressions in Equations (28) through (30) were used

to calculate the probability distribution of the states of the overall capability.

The developed fault-trees demonstrate a series system such that failure of each indicator in meeting the desired objective leads to the failure of the entire system. For example, the post-disruption fault-tree shows that intolerable state of the indicator “Time to the Nearest Hospital” gives rise to the intolerable state of the overall capability. The graphical feature of the fault-tree allows one to see the root causes of different outcomes and guide where to invest resources in order to improve the system performance. Further, it provides an understandable basis to debate the topology of the system and how different indicators can contribute to the overall capability.

Figure 6. Fault tree before disruption (University of Illinois).

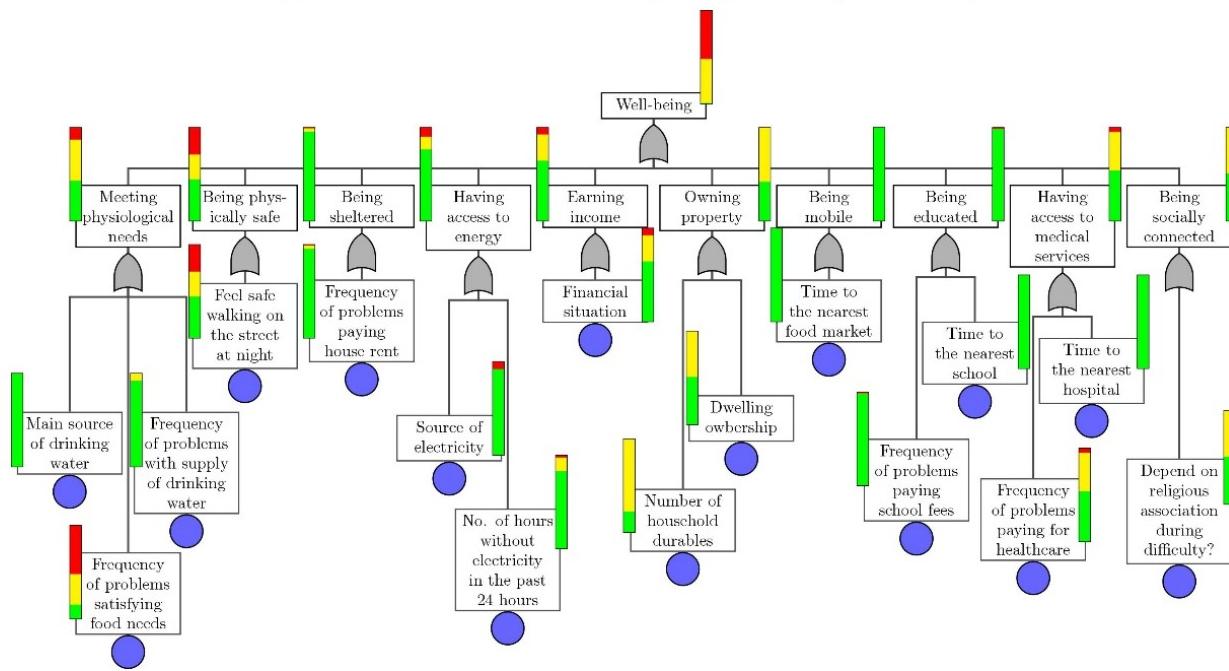
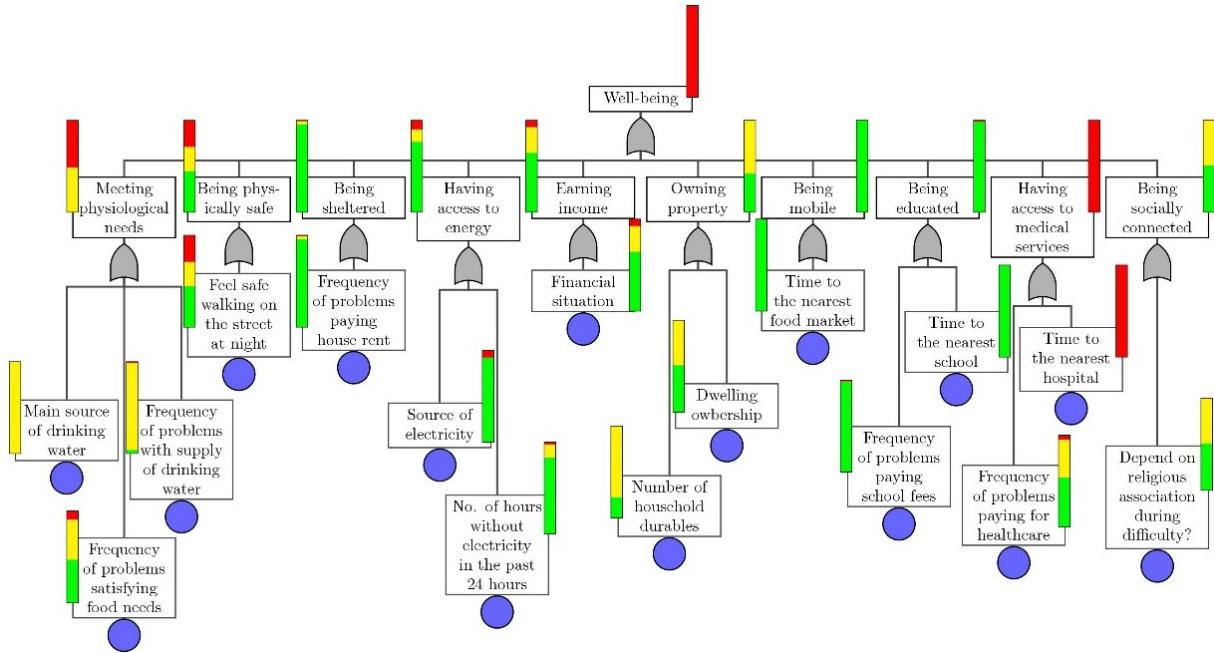


Figure 7. Fault tree after disruption (University of Illinois).



3.4 Probability distribution

In the following subsections, the expressions for the probability distribution of the states of each capability are derived.

3.4.1 Capability: “Meeting the Physiological Needs”

The expression for the probability of the acceptable state can be written as Equation (9):

$$\begin{aligned}
 \mathbf{P}(\mathcal{C}_1 = \text{Acc.}) &= \mathbf{P}\left[\bigcap_{j \in \{1,2,3\}} (\mathcal{I}_j = \text{Acc.})\right] \\
 &= \mathbf{P}(\mathcal{I}_1 = \text{Acc.}) \mathbf{P}(\mathcal{I}_2 = \text{Acc.} | \mathcal{I}_1 = \text{Acc.}) \mathbf{P}(\mathcal{I}_3 = \text{Acc.} | \mathcal{I}_2 = \text{Acc.}) \quad (9) \\
 &= \sum_{k=1}^2 \sum_{j=1}^2 \mathbf{1}_{\{\mathcal{I}_1=j\}} \mathbf{P}(I_2 = 1 | I_1 = j) \mathbf{P}(I_3 = k | I_2 = 1),
 \end{aligned}$$

where $\mathbf{1}_{\{\mathcal{I}_1=j\}}$ is the probability that $I_1 = j$; because $j \in \{1,2\}$, $\mathbf{1}_{\{\mathcal{I}_1=j\}}$ is the probability of the acceptable state; $\mathbf{P}(I_2 = 1 | I_1 = j)$ is the probability of the acceptable state of I_2 , given that $I_1 = j$; and $\mathbf{P}(I_3 = k | I_2 = 1)$ is the probability that $I_3 = k$ when $I_2 = 1$ is known, because $k \in \{1,2\}$, $\mathbf{P}(I_3 = k | I_2 = 1)$ is the probability of the acceptable state given that $I_2 = 1$. The category of the indicator I_1 is predicted using the infrastructure network analysis; the

probability of the predicted category is one, and the other states are zero. To obtain $\mathbf{P}(I_2 = 1 | I_1 = j)$ for a household (or a community), Equation (31) is used, along with the values of the regressors for the household (or community) and set $I_1 = j$. Similarly, to obtain $\mathbf{P}(I_3 = k | I_2 = l)$, Equation (32)¹ is used, along with the values of the regressors for the same household (or community) and set $I_2 = l$.

The probability of the intolerable state can be obtained as Equation (10):

$$\begin{aligned}
 \mathbf{P}(\mathcal{C}_1 = \text{Intol.}) &= \mathbf{P}\left[\bigcup_{j \in \{1,2,3\}} (\mathcal{I}_j = \text{Intol.})\right] \\
 &= 1 - \mathbf{P}\left[\bigcap_{j \in \{1,2,3\}} (\mathcal{I}_j = \overline{\text{Intol.}})\right] \\
 &= 1 - \mathbf{P}(\mathcal{I}_1 = \overline{\text{Intol.}}) \mathbf{P}(\mathcal{I}_2 = \overline{\text{Intol.}} | \mathcal{I}_1 = \overline{\text{Intol.}}) \mathbf{P}(\mathcal{I}_3 = \overline{\text{Intol.}} | \mathcal{I}_2 = \overline{\text{Intol.}}) \quad (10) \\
 &= 1 - \sum_{l=1}^3 \sum_{k=1}^2 \sum_{j=1}^3 \mathbf{1}_{\{I_1=j\}} \mathbf{P}(I_2 = k | I_1 = j) \mathbf{P}(I_3 = l | I_2 = k),
 \end{aligned}$$

where $\overline{\text{Intol.}}$ is the complement of the intolerable state which includes the acceptable and tolerable states. The calculation of the probability terms is similar to the terms in Equation (9). Accordingly, the probability of the tolerable state can be found as Equation (11):

$$\mathbf{P}(\mathcal{C}_1 = \text{Tolerable}) = 1 - \mathbf{P}(\mathcal{C}_1 = \text{Acceptable}) - \mathbf{P}(\mathcal{C}_1 = \text{Intolerable}). \quad (11)$$

3.4.2 Capability: “Being Physically Safe”

The achieved functioning in this capability is quantified by only one indicator. Hence, the calculation of the probability distribution of the capability’s states comes down to use of the developed predictive model, along with the designated states of the indicator Equation (12):

¹ Equations 31–42 are shown in Appendix B.

$$\begin{cases} \mathbf{P}(\mathcal{C}_2 = \text{Acceptable}) = \mathbf{P}(\mathcal{I}_4 = \text{Acceptable}) = \mathbf{P}(I_4 = 1), \\ \mathbf{P}(\mathcal{C}_2 = \text{Tolerable}) = \mathbf{P}(\mathcal{I}_4 = \text{Tolerable}) = \mathbf{P}(I_4 = 2), \\ \mathbf{P}(\mathcal{C}_2 = \text{Intolerable}) = \mathbf{P}(\mathcal{I}_4 = \text{Intolerable}) = \mathbf{P}(I_4 = 3), \end{cases} \quad (12)$$

where the values of the regressors of the households (or community) in Equation (33) are used to obtain the corresponding probabilities.

3.4.3 Capability: “Being Sheltered”

Similar to the previous capability, this one is also quantified by means of only one indicator. Accordingly, the probability distribution of the capability’s states is obtained in Equation (13):

$$\begin{cases} \mathbf{P}(\mathcal{C}_3 = \text{Acceptable}) = \mathbf{P}(\mathcal{I}_5 = \text{Acceptable}) = \sum_{k=1}^2 \mathbf{P}(I_5 = k), \\ \mathbf{P}(\mathcal{C}_3 = \text{Tolerable}) = \mathbf{P}(\mathcal{I}_5 = \text{Tolerable}) = \mathbf{P}(I_5 = 3), \\ \mathbf{P}(\mathcal{C}_3 = \text{Intolerable}) = \mathbf{P}(\mathcal{I}_5 = \text{Intolerable}) = \mathbf{P}(I_5 = 4), \end{cases} \quad (13)$$

where Equation (34) is used to obtain $\mathbf{P}(I_5 = 1), \dots, \mathbf{P}(I_5 = 4)$.

3.4.4 Capability: “Having Access to Energy”

The probability distribution of Equation (14):

$$\begin{aligned} \mathbf{P}(\mathcal{C}_4 = \text{Acceptable}) &= \left[\bigcap_{j \in \{6,7\}} \mathbf{P}(\mathcal{I}_j = \text{Acceptable}) \right] \\ &= \mathbf{P}(\mathcal{I}_6 = \text{Acceptable}) \mathbf{P}(\mathcal{I}_7 = \text{Acceptable}) \\ &= \sum_{l=1}^4 \mathbf{P}(I_6 = 1 | I_5 = l) \mathbf{P}(I_5 = l) \\ &\quad \times \sum_{l=1}^4 \sum_{k=1}^3 \mathbf{P}(I_7 = 1 | I_2 = k, I_5 = l) \mathbf{P}(I_2 = k) \mathbf{P}(I_5 = l), \end{aligned} \quad (14)$$

where Equation (35) was used to calculate $\mathbf{P}(I_6 = 1 | I_5 = l)$, in which $I_5 = l$ is set; use Equation (34) to obtain $\mathbf{P}(I_5 = l)$; use Equation (36) to obtain $\mathbf{P}(I_7 = 1 | I_2 = k, I_5 = l)$, in which $I_2 = k$ and $I_5 = l$ are set; and use Equation (31) to obtain $\mathbf{P}(I_2 = k)$.

Next, the probability of the intolerable state is calculated as Equation (15):

$$\begin{aligned}
 \mathbf{P}(\mathcal{C}_4 = \text{Intolerable}) &= \mathbf{P}\left[\bigcup_{j \in \{6,7\}} (\mathcal{I}_j = \text{Intolerable})\right] \\
 &= 1 - \mathbf{P}\left[\bigcap_{j \in \{6,7\}} (\mathcal{I}_j = \overline{\text{Intolerable}})\right] \\
 &= 1 - \mathbf{P}(\mathcal{I}_6 = \overline{\text{Intolerable}}) \mathbf{P}(\mathcal{I}_7 = \overline{\text{Intolerable}}) \\
 &= 1 - \sum_{l=1}^4 \mathbf{P}(I_6 = l | I_5 = l) \mathbf{P}(I_5 = l) \\
 &\quad \times \sum_{l=1}^4 \sum_{k=1}^3 \sum_{j=1}^2 \mathbf{P}(I_7 = j | I_2 = k, I_5 = l) \mathbf{P}(I_2 = k) \mathbf{P}(I_5 = l).
 \end{aligned} \tag{15}$$

Finally, the probability of the tolerable state can be written as Equation (16):

$$\mathbf{P}(\mathcal{C}_4 = \text{Tolerable}) = 1 - \mathbf{P}(\mathcal{C}_4 = \text{Acceptable}) - \mathbf{P}(\mathcal{C}_4 = \text{Intolerable}). \tag{16}$$

3.4.5 Capability: “Earning Income”

Because the capability is quantified by only one indicator, the probability distribution of the capability can be simply obtained as Equation (17):

$$\begin{cases} \mathbf{P}(\mathcal{C}_5 = \text{Acceptable}) = \mathbf{P}(\mathcal{I}_8 = \text{Acceptable}) = \sum_{k=3}^4 \mathbf{P}(I_8 = k), \\ \mathbf{P}(\mathcal{C}_5 = \text{Tolerable}) = \mathbf{P}(\mathcal{I}_8 = \text{Tolerable}) = \mathbf{P}(I_8 = 2), \\ \mathbf{P}(\mathcal{C}_5 = \text{Intolerable}) = \mathbf{P}(\mathcal{I}_8 = \text{Intolerable}) = \mathbf{P}(I_8 = 1), \end{cases} \tag{17}$$

where Equation (37) is used to calculate $\mathbf{P}(I_8 = 1), \dots, \mathbf{P}(I_8 = 4)$.

3.4.6 Capability: “Owning Property”

The joint distribution of the two capability indicators determines the probability distribution of the capability. First, the probability of the acceptable state is obtained as Equation (18):

$$\begin{aligned}
 \mathbf{P}(\mathcal{C}_6 = \text{Acceptable}) &= \left[\bigcap_{j \in \{9, 10\}} \mathbf{P}(\mathcal{I}_j = \text{Acceptable}) \right] \\
 &= \mathbf{P}(\mathcal{I}_9 = \text{Acceptable}) \mathbf{P}(\mathcal{I}_{10} = \text{Acceptable}) \\
 &= \sum_{k=4}^6 \mathbf{P}(I_9 = k) \times \mathbf{P}(I_{10} = 1),
 \end{aligned} \tag{18}$$

where Equations (38) and (39) are used to obtain $\mathbf{P}(I_9 = k)$ and $\mathbf{P}(I_{10} = 1)$. Because for both indicators the intolerable state is not defined, the associated probability would be uniformly 0 (i.e., $\mathbf{P}(\mathcal{C}_6 = \text{Intolerable}) = 0$). Accordingly, the probability of the tolerable state can be written as Equation (19):

$$\mathbf{P}(\mathcal{C}_6 = \text{Tolerable}) = 1 - \mathbf{P}(\mathcal{C}_6 = \text{Acceptable}). \tag{19}$$

3.4.7 Capability: “Being Mobile”

There is only one indicator to quantify this capability, and it is predicted by using the infrastructure network analysis. Thus, the probability distribution can be simply written as Equation (20):

$$\begin{cases} \mathbf{P}(\mathcal{C}_7 = \text{Acceptable}) = \mathbf{P}(\mathcal{I}_{11} = \text{Acceptable}) = \sum_{k=1}^3 \mathbf{1}_{\{I_{11}=k\}}, \\ \mathbf{P}(\mathcal{C}_7 = \text{Tolerable}) = \mathbf{P}(\mathcal{I}_{11} = \text{Tolerable}) = \mathbf{1}_{\{I_{11}=4\}}, \\ \mathbf{P}(\mathcal{C}_7 = \text{Intolerable}) = \mathbf{P}(\mathcal{I}_{11} = \text{Intolerable}) = \mathbf{1}_{\{I_{11}=5\}}. \end{cases} \tag{20}$$

3.4.8 Capability: “Being Educated”

The two capability indicators are combined to obtain the probability distribution of the capability’s states. First, the probability of the acceptable state is written as Equation (21):

$$\begin{aligned}
\mathbf{P}(\mathcal{C}_8 = \text{Acceptable}) &= \left[\bigcap_{j \in \{12,13\}} \mathbf{P}(\mathcal{I}_j = \text{Acceptable}) \right] \\
&= \mathbf{P}(\mathcal{I}_{12} = \text{Acceptable}) \mathbf{P}(\mathcal{I}_{13} = \text{Acceptable}) \\
&= \sum_{k=1}^3 \mathbf{1}_{\{I_{12}=k\}} \times \sum_{k=1}^2 \mathbf{P}(I_{13} = k)
\end{aligned} \tag{21}$$

where I_{12} is obtained from the infrastructure network analysis and I_{13} is predicted using Equation(40). Next, the probability of the intolerable state is obtained as Equation (22):

$$\begin{aligned}
\mathbf{P}(\mathcal{C}_8 = \text{Intolerable}) &= \mathbf{P}\left[\bigcup_{j \in \{12,13\}} (\mathcal{I}_j = \overline{\text{Intolerable}})\right] \\
&= 1 - \mathbf{P}\left[\bigcap_{j \in \{12,13\}} (\mathcal{I}_j = \overline{\text{Intolerable}})\right] \\
&= 1 - \mathbf{P}(\mathcal{I}_{12} = \overline{\text{Intolerable}}) \mathbf{P}(\mathcal{I}_{13} = \overline{\text{Intolerable}}) \\
&= 1 - \sum_{k=1}^4 \mathbf{1}_{\{I_{12}=k\}} \times \sum_{k=1}^3 \mathbf{P}(I_{13} = k).
\end{aligned} \tag{22}$$

Subsequently, the probability of the tolerable state can be written as Equation (23):

$$\mathbf{P}(\mathcal{C}_8 = \text{Tolerable}) = 1 - \mathbf{P}(\mathcal{C}_8 = \text{Acceptable}) - \mathbf{P}(\mathcal{C}_8 = \text{Intolerable}). \tag{23}$$

3.4.9 Capability: “Having Access to Medical Services”

Similar to the previous capability, this one is consisting of two indicators. The probability of the acceptable state of the capability can be written as Equation (24):

$$\begin{aligned}
\mathbf{P}(\mathcal{C}_9 = \text{Acceptable}) &= \left[\bigcap_{j \in \{14, 15\}} \mathbf{P}(\mathcal{I}_j = \text{Acceptable}) \right] \\
&= \mathbf{P}(\mathcal{I}_{14} = \text{Acceptable}) \mathbf{P}(\mathcal{I}_{15} = \text{Acceptable}) \\
&= \sum_{k=1}^3 \mathbf{1}_{\{I_{14}=k\}} \times \sum_{k=1}^2 \mathbf{P}(I_{15} = k),
\end{aligned} \tag{24}$$

where I_{14} is obtained from the infrastructure network analysis and I_{15} is predicted by using Equation(41). Next, the probability of the intolerable state is obtained from Equation (25):

$$\begin{aligned}
\mathbf{P}(\mathcal{C}_9 = \text{Intolerable}) &= \mathbf{P}\left[\bigcup_{j \in \{14, 15\}} (\mathcal{I}_j = \overline{\text{Intolerable}})\right] \\
&= 1 - \mathbf{P}\left[\bigcap_{j \in \{14, 15\}} (\mathcal{I}_j = \overline{\text{Intolerable}})\right] \\
&= 1 - \mathbf{P}(\mathcal{I}_{14} = \overline{\text{Intolerable}}) \mathbf{P}(\mathcal{I}_{15} = \overline{\text{Intolerable}}) \\
&= 1 - \sum_{k=1}^4 \mathbf{1}_{\{I_{14}=k\}} \times \sum_{k=1}^3 \mathbf{P}(I_{15} = k).
\end{aligned} \tag{25}$$

Finally, the probability of the tolerable state can be written as Equation (26):

$$\mathbf{P}(\mathcal{C}_9 = \text{Tolerable}) = 1 - \mathbf{P}(\mathcal{C}_9 = \text{Acceptable}) - \mathbf{P}(\mathcal{C}_9 = \text{Intolerable}). \tag{26}$$

3.4.10 Capability: “Being Socially Connected”

The achieved functioning, this capability is quantified by means of a binary indicator. Thus, the capability has only two states, which are the acceptable and tolerable states. The corresponding probabilities can be obtained as Equation (27):

$$\begin{cases} \mathbf{P}(\mathcal{C}_{10} = \text{Acceptable}) = \mathbf{P}(\mathcal{I}_{16} = \text{Acceptable}) = \mathbf{P}(I_{16} = 1), \\ \mathbf{P}(\mathcal{C}_{10} = \text{Tolerable}) = \mathbf{P}(\mathcal{I}_{16} = \text{Tolerable}) = \mathbf{P}(I_{16} = 2), \end{cases} \tag{27}$$

where Equation (42) is used to calculate $\mathbf{P}(I_{16} = 1)$ and $\mathbf{P}(I_{16} = 2)$.

3.4.11 Overall capability

In the next step, the probability distribution of different capabilities is combined according to the fault-tree topology to obtain the probability distribution of the overall capability. The overall capability is modeled as a series system, such that the probability distribution of the states can be written as Equation (28):

$$\begin{cases} \mathbf{P}(\mathcal{C} = \text{Acceptable}) = \mathbf{P}\left[\bigcap_{r=1}^{10} \mathbf{P}(\mathcal{C}_r = \text{Acceptable})\right], \\ \mathbf{P}(\mathcal{C} = \text{Intolerable}) = \mathbf{P}\left[\bigcup_{r=1}^{10} \mathbf{P}(\mathcal{C}_r = \text{Intolerable})\right], \\ \mathbf{P}(\mathcal{C} = \text{Tolerable}) = 1 - \mathbf{P}(\mathcal{C} = \text{Acceptable}) - \mathbf{P}(\mathcal{C} = \text{Intolerable}). \end{cases} \quad (28)$$

First, the probability of the acceptable state is calculated. The calculation involves a 16-fold summation of the joint probability distribution of the indicators. However, the statistical independence of a subset of indicators is of benefit. The final expression for the probability of the acceptable state can be written as Equation (29):

$$\begin{aligned} \mathbf{P}\left[\bigcap_{r=1}^{10} \mathbf{P}(\mathcal{C}_r = \text{Acceptable})\right] &= \mathbf{P}\left[\bigcap_{j=1}^{16} \mathbf{P}(\mathcal{I}_j = \text{Acceptable})\right] \\ &= \sum_{l=2}^6 \sum_{k=1}^2 \sum_{j=1}^2 \mathbf{1}_{\{I_1=j\}} \mathbf{P}(I_2 = 1 | I_1 = j) \mathbf{P}(I_9 = l | I_1 = j) \mathbf{P}(I_{10} = 1 | I_1 = j) \\ &\quad \mathbf{P}(I_{13} = k | I_1 = j) \times \sum_{m=1}^2 \sum_{l=1}^3 \sum_{k=1}^2 \sum_{j=1}^2 \mathbf{1}_{\{I_{11}=l\}} \mathbf{P}(I_3 = j | I_2 = 1, I_{11} = l) \mathbf{P}(I_5 = k | I_{11} = l) \quad (29) \\ &\quad \mathbf{P}(I_6 = 2 | I_5 = k) \mathbf{P}(I_7 = 1 | I_2 = 1, I_5 = k) \mathbf{P}(I_{15} = m | I_{11} = l) \\ &\quad \times \sum_{j=1}^3 \mathbf{1}_{\{I_{12}=j\}} \mathbf{P}(I_4 = 1 | I_{12} = j) \times \sum_{k=1}^3 \sum_{j=3}^4 \mathbf{1}_{\{I_{14}=k\}} \mathbf{P}(I_8 = j | I_{14} = k) \mathbf{P}(I_{16} = 1 | I_{14} = k). \end{aligned}$$

The probability of the intolerable state can be written as Equation (30):

$$\begin{aligned}
& \mathbf{P}\left[\bigcup_{r=1}^{10} \mathbf{P}(\mathcal{C}_r = \text{Intolerable})\right] = 1 - \mathbf{P}\left[\bigcap_{j=1}^{10} \mathbf{P}(\mathcal{C}_r = \overline{\text{Intolerable}})\right] \\
& = 1 - \mathbf{P}\left[\bigcap_{j=1}^{16} \mathbf{P}(\mathcal{I}_j = \overline{\text{Intolerable}})\right] \\
& = 1 - \sum_{o=1}^3 \sum_{n=1}^4 \sum_{m=1}^2 \sum_{l=1}^3 \sum_{k=1}^3 \sum_{j=1}^2 \mathbf{1}_{\{I_{11}=n\}} \mathbf{P}(I_2 = j) \mathbf{P}(I_3 = k | I_2 = j, I_{11} = n) \mathbf{P}(I_5 = l | I_{11} = n) \quad (30) \\
& \mathbf{P}(I_6 = 2 | I_5 = l) \mathbf{P}(I_7 = m | I_2 = j, I_5 = l) \mathbf{P}(I_{15} = o | I_{11} = n) \\
& \times \sum_{k=1}^4 \sum_{j=1}^2 \mathbf{1}_{\{I_{12}=k\}} \mathbf{P}(I_4 = j | I_{12} = k) \times \sum_{k=1}^4 \sum_{j=2}^4 \mathbf{1}_{\{I_{14}=k\}} \mathbf{P}(I_8 = j | I_{14} = k) \times \sum_{j=1}^3 \mathbf{P}(I_{13} = j).
\end{aligned}$$

The derived expressions for the probabilities of the acceptable and intolerable states can be used in Equation (28) to obtain the probability of the tolerable state.

See Appendix B, *Probabilistic Predictive Models of Indicator Indices*, for an explanation of the probabilistic predictive models (Equations 31–42) that were developed for the indicator indices of the selected capabilities.

4 Conclusion

4.1 Summary of efforts

This research used a capability approach to quantify the societal impact of disruptions to civil infrastructure. A set of 10 pertinent capabilities was selected to capture specific social, cultural, and economic aspects of individuals' well-being. This list includes the following capabilities:

1. Meeting the physiological needs.
2. Being physically safe.
3. Being sheltered.
4. Having access to energy.
5. Earning income.
6. Owning property.
7. Being mobile.
8. Being educated.
9. Having access to medical services.
10. Being socially connected.

Because these capabilities are not directly measurable, a set of 16 indicators was selected to quantify the corresponding capabilities (See Table 1). For example, to quantify the achieved functionings of the capability of "Meeting the Physiological Needs," three indicators were selected:

1. "Main Source of Drinking Water,"
2. "Frequency of Problems with Supply of Drinking Water," and
3. "Frequency of Problems Satisfying Food Needs."

The rationale behind selecting each indicator was discussed, and their significance and relevance were justified based on an extensive literature review and statistical analyses of different datasets. The third step involves scaling the indicators to create indices. The indicator indices vary in the range [0,1], where 0 is the minimum achievement and 1 is the maximum. The values/categories of the indicators (or their indices) for each individual/household depend on the status of the infrastructure systems to deliver vital needs like potable water, the wealth to satisfy basic needs, and the social structure of communities. In order to quantitatively explore such relations, in the fourth step, probabilistic predictive models of the indicator (indices) were developed. An important consideration in developing

the predictive models is to account for various sources of uncertainty surround the quantification of the indicator (indices). For example, there is uncertainty in predicting the value/category of indicator (indices) in the future. The values/categories of different indicators collectively determine the state of the corresponding capability, which could be in principle acceptable, tolerable, or intolerable. In the last step, a system of capability indicators was created, and the methods of system reliability analysis were used to obtain the probability distribution of the capability states.

As an application of the proposed formulation, the capabilities of households living in the urban areas of Maiduguri, Nigeria, was quantified. The disruptive event scenario used includes the failure of a fuel depot, which in turn cascades to a water treatment plant. To predict the values/categories of different indicator (indices), results of infrastructure network analysis were used along with the available census data in the predictive models. To determine the topology of the system of capability indicators, a fault-tree analysis was used (see Figure 6 and Figure 7). Given an unfavorable state of the system as a top event, the fault-tree systematically explores the root causes of observing the top event. The analytical expressions derived for the probability distribution of each capability were solved for each capability.

4.2 Results

The results are summarized as a series of maps that show the average achievements of the households in Maiduguri in terms of each of the 10 capabilities as well as their overall aggregated capability (see Appendix C, Figures C11–C21).

Future research could be conducted in a number of areas incorporating the SMART documents in information and data gathering either at a survey level or observation level. Data Guides and Field Guides (forthcoming from ERDC-CERL in 20017) have been developed to assist SMART document users to capture relevant individual and societal detailed information based on the access, availability, and use of the five infrastructure nodes within this study (communication, electricity, food security, transportation, and water).

4.3 Scenario

The proposed framework is used, along with the collected data for the households in the urban area of Maiduguri, to calculate the spatial distribution of well-being in terms of each capability and overall capabilities. The predictive models developed for indicators are calibrated using the data for the households. However, the information about the location of the households, used for calibration, is available only at the LGA level. The result of the infrastructure network analysis, required to predict a subset of indicators and regressors, is available at the community level, where communities are smaller units within each LGA. To be consistent in the prediction of capabilities, the community was set as the target unit of analysis. The averaged values of the regressors at the LGA level would apply to all communities within the LGA, unless the value of the regressors from the infrastructure network analysis that gives the values at the community level can be obtained. Furthermore, the network analysis is calibrated with the predicted quantities (i.e., regressors/indicators) at the LGA level, before the occurrence of any disruptive events, being similar to those from the database.

A scenario was developed wherein a disruption impacts the fuel depot and the southeast water treatment plant and the failure propagation and social impacts were investigated. The fuel depot power substation is a critical node that supports a variety of other infrastructure nodes, including transportation, electricity, and water. The water treatment plant provides potable water to a large portion of the city. After applying the model, the before and after disruption results were identified for the capability of “Meeting Physiological Needs.” Figure 8 shows the infrastructure nodes before disruption and the level of access to that node and Figure 9 shows the infrastructure nodes after disruption and the cascading effect of the impacts to social well-being in terms of access to water and access to food.

Figure 8. Example of infrastructure nodes before disruption and level of access to the node (initial source of water) (ERDC-CERL).

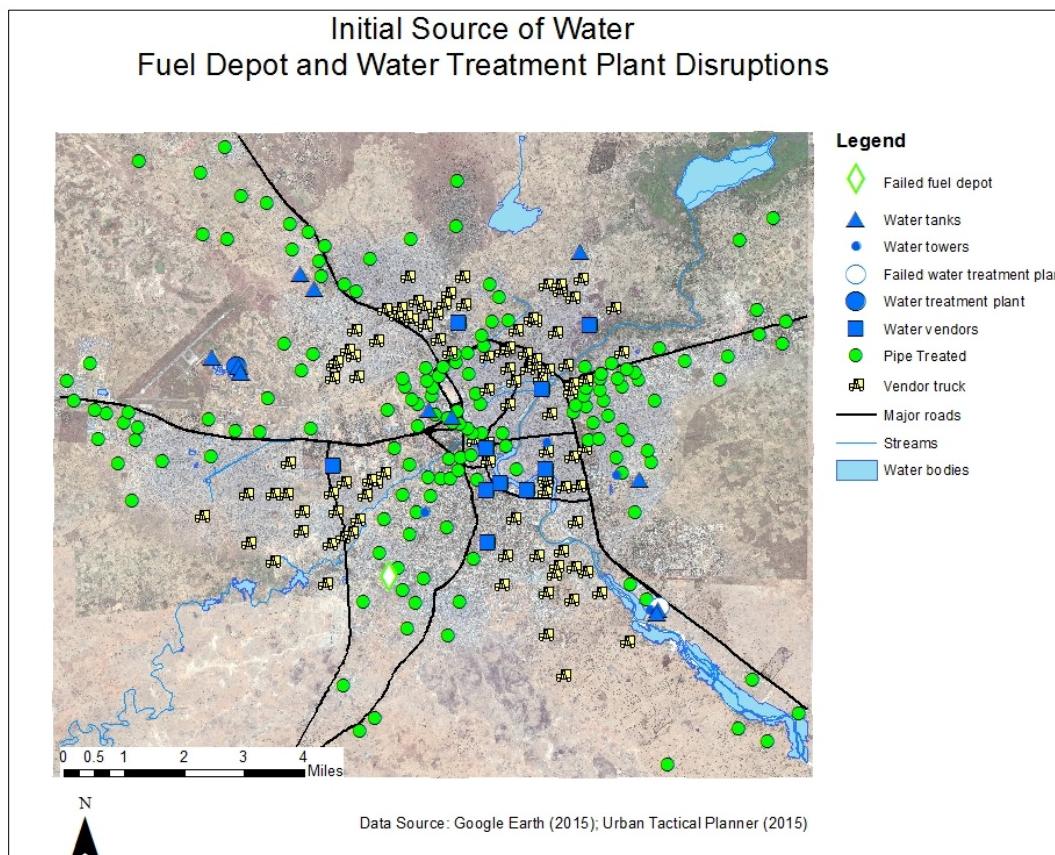
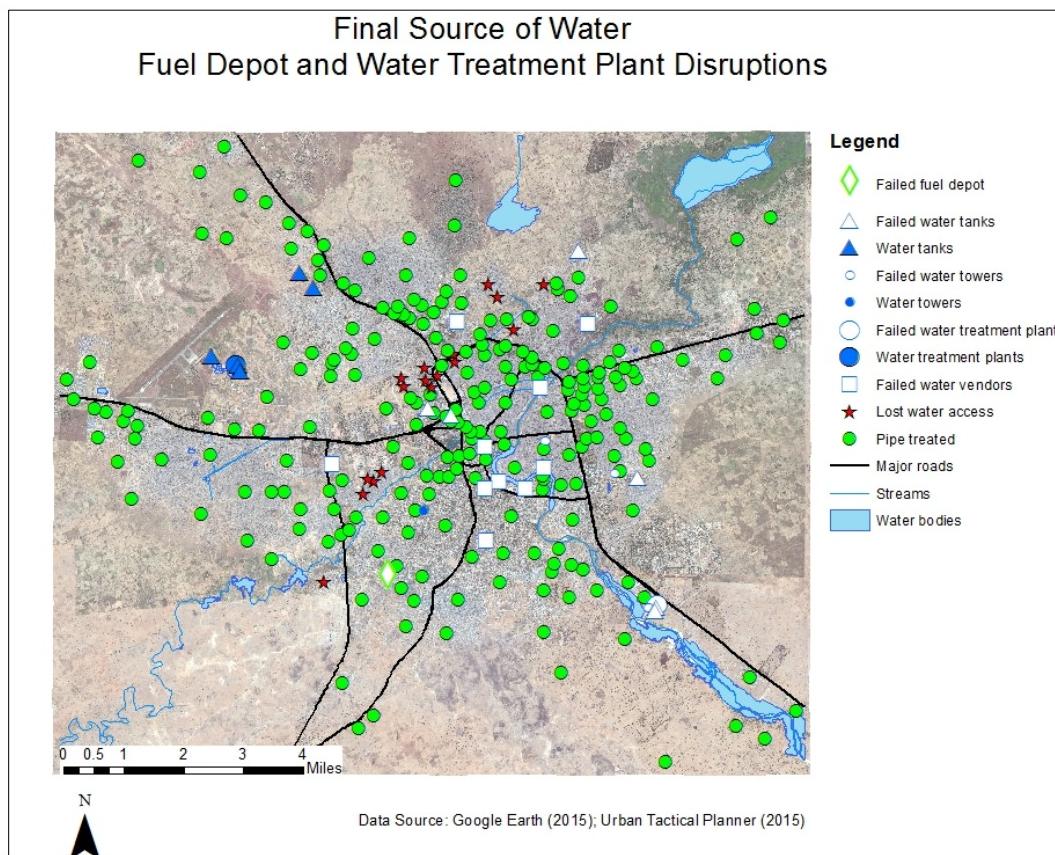


Figure 9. Example of infrastructure nodes after disruption and the cascading effect of the impacts to social well-being (final source of water) (ERDC-CERL).



The impacts are that all electricity transformers are shut down, the electricity network is disabled, while only local electrical generators can work based on fuel, providing very limited (and expensive) power supply to nearby communities. Furthermore, the water network is also disrupted, while only local water vendors can pump water from wells.

In terms of meeting physiological needs, the indicators represented include access to water and access to food (see Figure 10–Figure 13). The water distribution system is impacted by requiring individuals to go to an alternative source to obtain water. Access cost therefore increases making it more difficult to meet physiological needs. Depending on the area, access to food is compromised—restaurants do not have power, markets can't keep food fresh, and agriculture suffers from lack of water source. The transportation network is ultimately effected, and access to food and water is compromised. Three indicators were selected to address physiological needs:

1. “Main Source of Drinking Water,”
2. “Frequency of Problems with Supply of Drinking Water,” and
3. “Frequency of Problems Satisfying Food Needs.”

Figure 10. Example of infrastructure nodes before disruption and level of access to the node (initial source of water) (ERDC-CERL).

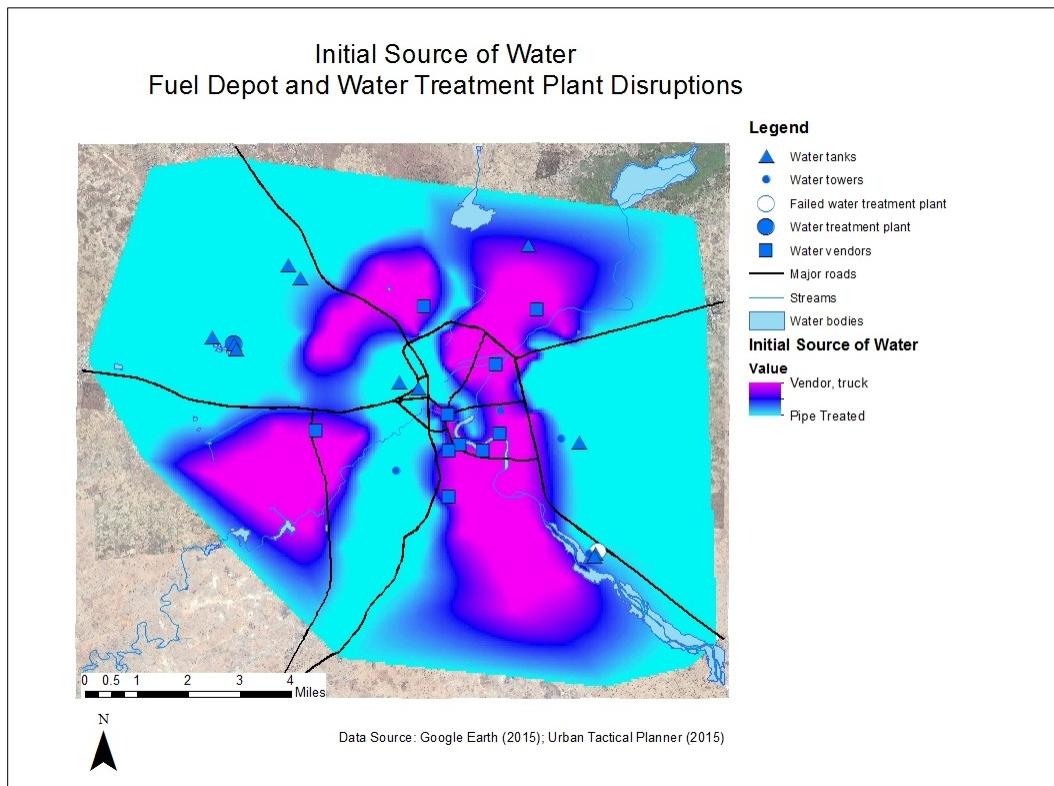


Figure 11. Example of infrastructure nodes after disruption and the cascading effect of the impacts to social well-being (final source of water) (ERDC-CERL).

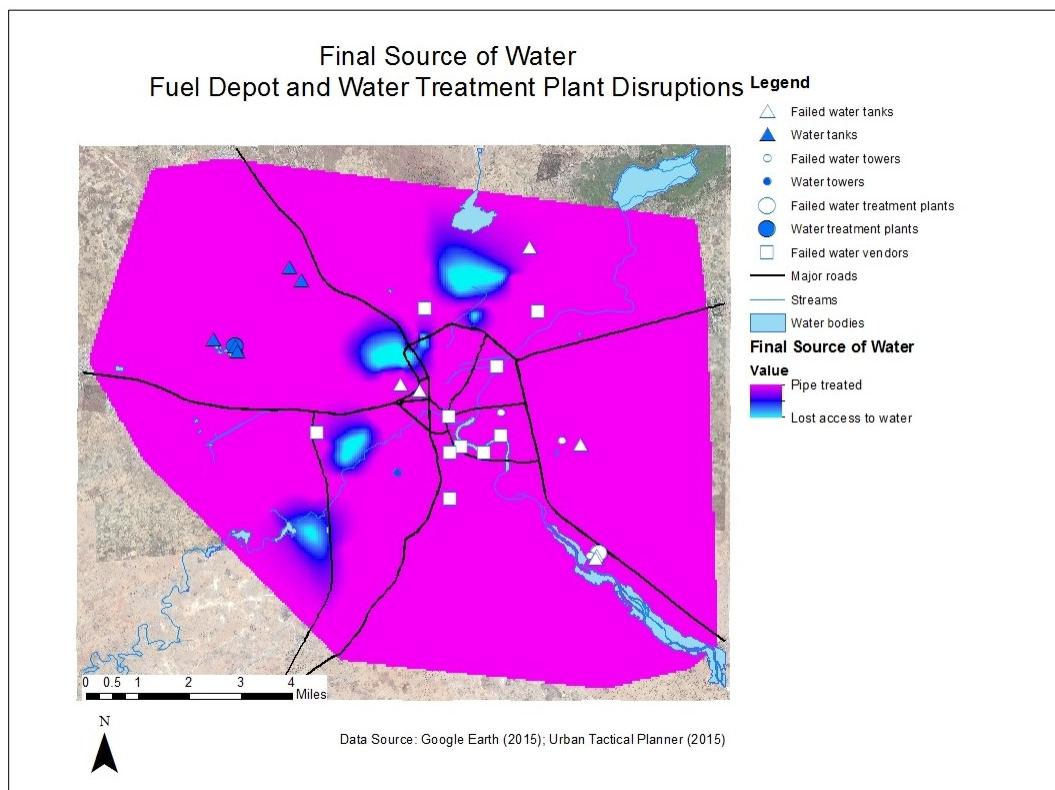


Figure 12. Example of infrastructure nodes before disruption and level of access to the node (initial time to food) (ERDC-CERL).

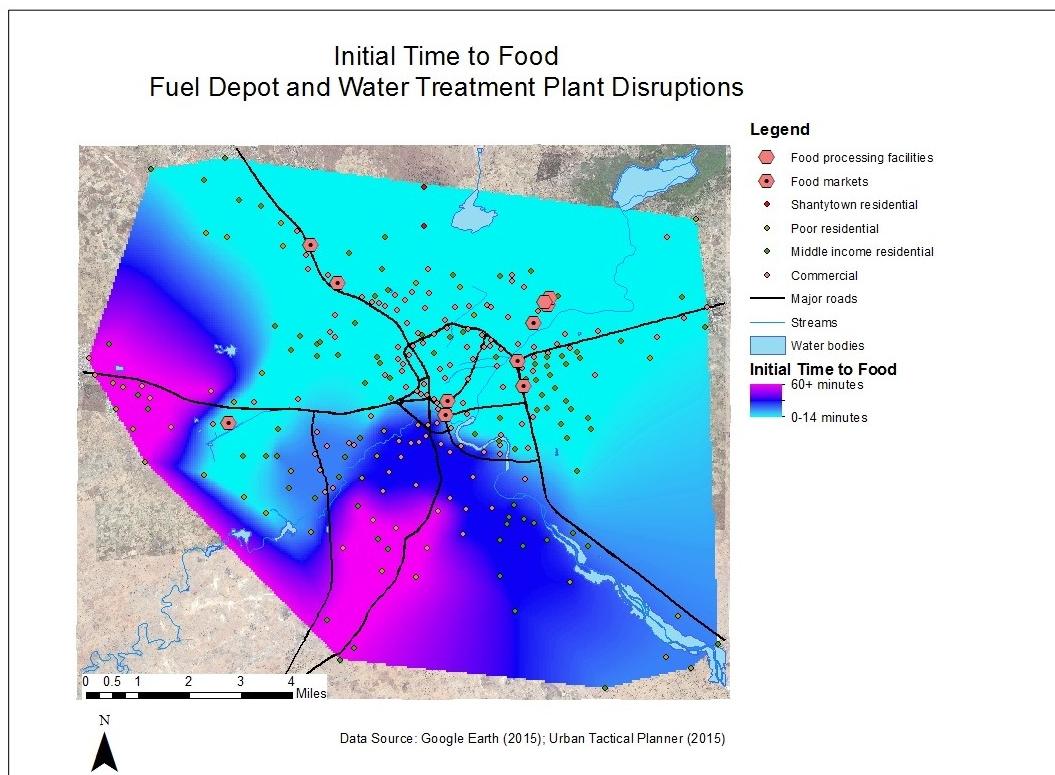
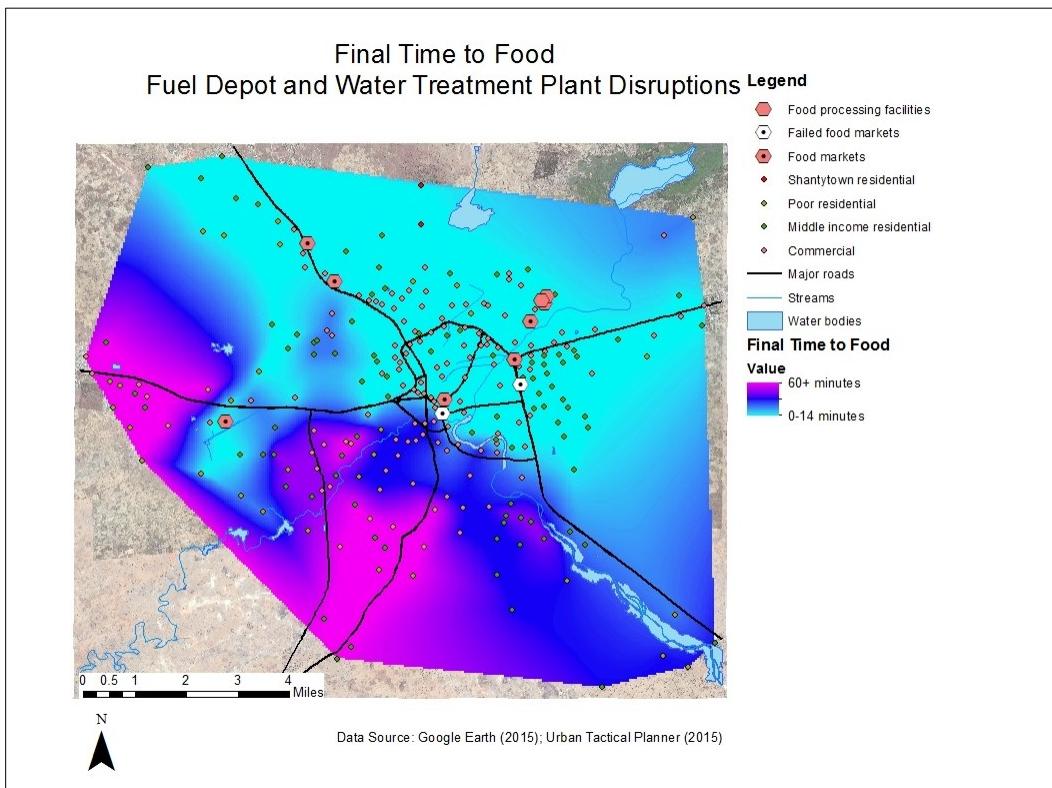


Figure 13. Example of infrastructure nodes after disruption, and the cascading effect of the impacts to social well-being (final time to food) (ERDC-CERL).



The capabilities of households in different communities are evaluated in an average sense. For this purpose, the three capability states were scored as $\{0, 0.5, 1\}$, respectively, for intolerable, tolerable, and acceptable states. Combining the scored state with the corresponding calculated probabilities will estimate the averaged values. Based on these calculations, a series of maps was created (see Appendix C, Figures C11–C23) that show the averaged capabilities before and after the disruption. The post-disruption capabilities represent the immediate aftermath condition. To predict the long-term effects, further information is required about the restoration process and how fast the states of capabilities would be improved. From the obtained results, it can be observed that there are only three capabilities that are changed with respect to the pre-disruption situation. However, when evaluating the impact of a disruption, it is important to account for all the defined capabilities and not to focus only on those whose values have changed. The impact of a disruption in two communities subject to the same change in a subset of capabilities, but being noticeably different in terms of other capabilities, would not be similar. Furthermore, when the capabilities are statistically dependent, the improvement in one capability can affect the others as well. Hence, the decision about where to invest the

limited resources would be different whether or not the state of unchanged capabilities were accounted for.

Appendix A: Capability and Indicator Descriptions

Capability: “Meeting the Physiological Needs”

This capability represents one of the two facets within the concept of meeting physiological needs. In this study, two physiological needs were considered: the need for potable water and the need for food (as identified in Table A1). These two needs are fundamental for survival.

Table A1. Capability of “Meeting the Physiological Needs” (NBS 2006).

Indicator	NBS Question	Answer
Main Source of Drinking Water	What is the main source of drinking water?	Pipe-borne water, treated. Pipe-borne water, untreated. Bore hole or hand pump. Protected well. Unprotected well. Rain water. River, lake, or pond. Vendor, truck. Other.
Frequency of Problems with Supply of Drinking Water	Are there any problems with supply of drinking water?	No. Yes, during dry season. Yes, frequently.
Frequency of Problems Satisfying Food Needs	Are there any problems with satisfying food needs?	Never. Seldom. Sometimes. Often. Always.

Indicator: “Main Source of Drinking Water”

As outlined by Table A1, the first indicator of the capability of “Meeting the Physiological Needs” is “Main Source of Drinking Water.” This indicator is used to refer to the aspect of access to potable water.

Every human being needs clean drinking water to sustain her/his life, bodily health, and other central human capabilities (Nussbaum 2007, 23). The

quality of drinking water source defines the level of an individual's capability to meet physiological needs, especially in Sub-Saharan Africa (Akali et al. 2014). According to the World Health Organization (WHO)/United Nations Children's Emergency Fund (UNICEF) Joint Monitoring Programme (JMP), drinking water sources can be categorized into four groups, as given below:

1. Piped water on premises.
2. Other improved sources, including public tap or standpipe, tubewell or borehole, protected spring, protected dug well, and rainwater collection.
3. Unimproved sources, including unprotected dug well, unprotected spring, cart with small tank or drum, tanker truck, and bottled water.
4. Surface water (UNICEF and WHO 2012, 33; 2015, 50).

Here, the rationale for the JMP's classifying bottled water as an "unimproved" drinking water source is due to the observation that "bottled water alone does not provide [an] affordable supply of water for all domestic needs" (UNICEF and WHO 2011, 45).

In Nigeria, the borehole and the treated utility piped water are the most reliable drinking water sources, while water from vehicle tankers and protected dug wells is also decent but of lower quality (Ince et al. 2010, 40). The operational practices of the vehicle tankers might affect the water quality, while "protected dug wells are normally managed by individual households", and their quality relies on the hygiene conditions of the managing households (Ince et al. 2010, 40).

Based on these universal and local conditions, a protocol was developed to determine the scale that represents the corresponding levels of quality of drinking water sources identified within the dataset (NBS 2006). Based on the UNICEF/WHO JMP's taxonomy of drinking water sources (UNICEF and WHO 2012, 33; 2015, 50), the sources were ranked from 1 to 4, respectively. Following the local assessment of drinking-water quality in Nigeria (Ince et al. 2010, 40), borehole and treated utility piped water were coded 1, vehicle tanker and protected dug well were coded 2, and the other drinking water sources in Maiduguri were coded 3. Through summing up these two sets of integer scores, a scale of drinking water sources was derived, as listed below in Table A2.

Table A2. Drinking water source priority protocol (ERDC-CERL).

Group	Source	UNICEF/WHO JMP Score	Local Assessment Score	Final Score
Very Good	Pipe-borne water, treated	1	1	2
Good	Bore hole or hand pump	2	1	3
Decent	Protected well	2	2	4
	Vendor, truck	3	2	5
	Rain water	2	3	5
Poor	Pipe-borne water, untreated	3	3	6
	Unprotected well	3	3	6
Very Poor	River, lake, or pond	4	3	7
	Other	4	3	7

Disruptions in water supply/infrastructure will possibly negatively impact drinking water sources. The value of the indicator “Main Source of Drinking Water” is likely to shift toward the less desirable after a disruption occurs. However, for the residents whose drinking water sources are already poor, the relief drinking water supply, such as sachet and bottled water provided immediately to the affected areas, might temporarily increase those residents’ level of well-being by having access to a more desirable source of potable water, reflected by the indicator “Main Source of Drinking Water.”

Indicator: “Frequency of Problems with the Supply of Drinking Water”

The second indicator manifesting the capability of “Meeting the Physiological Needs” is “Frequency of Problems with the Supply of Drinking Water”, as illustrated in Table A1.

During a disruption or in a disaster situation, such as after an earthquake (Mileti 1999, 91), tsunami (CDC [Centers for Disease Control] 2014), hurricane (EPA 2005), flood (EPA 2015), massive explosion (Colon and Ford 2015), or terror event (Gleick 2006), the drinking water sources within the impact area are likely to be damaged or polluted, so the affected locals might face a shortage of drinking water after the disruption. In Maiduguri, one of the main water sources is the Alau Reservoir, which is located 14 km

southeast of the city. The Alau Reservoir, along with a treatment plant about 100 m from University of Maiduguri Gate II, has become one of the main sources of drinking water for the city of Maiduguri (World Bank 1996; Dammo and Sangodoyin 2014, 387).

However, a drinking water shortage could still occur if the Alau Reservoir were to dry up during the dry season from January to July (e.g., World Bank 1996, 4). Moreover, recent local studies show that beyond-tolerance-levels for lead and pesticide concentrations have been detected in the tissues of fish samples from the Alau Reservoir (Dimari et al. 2008; Akan et al. 2013). Also, researchers have detected high concentrations of nitrate, phosphate, and *Escherichia coli* in the Alau Reservoir (Dammo and Sangodoyin 2014). Thus, it is anticipated that when a severe disruption occurs to the local community, the impact will negatively affect the existing issues with the supply of drinking water in the city of Maiduguri. The impact could immediately increase the frequency of problems with the supply of drinking water that a local household would face. If one household's frequency of problems with supply of drinking water is already high, it is anticipated that a disruption could exacerbate this situation.

Indicator: “Frequency of Problems Satisfying Food Needs”

As displayed in Table A1, the third indicator of the capability of “Meeting the Physiological Needs” is “Frequency of Problems Satisfying Food Needs.” This indicator represents the availability of food, access to food, and local food security.

Food security is characterized as a “situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life” (FAO [Food and Agriculture Organization of the United Nations] 1996; FAO 2001, 49). Food security is not only related to the supply of food or food availability, but also it is dependent on the entitlement of the household that could guarantee the food to be accessible to the household (Sen 1981; FAO 2003, 28).

When a disruption occurs, the impact could damage livestock, crops, and farming facilities (Alexander 1993, 329; Tobin and Montz 1997, 245; Mileti 1999, 91). It could also lead to household income loss due to destruction of workplaces (Mileti 1999, 98), thus disrupting the entitlements of the local residents and subsequently the local food consumption.

In Borno State, drought and desertification are perennial hazards that impact the local agricultural yield (Seneviratne 2002, 101). The recent terror event risks related to the Boko Haram (BH) extremist religious sect have added one more layer of threat to the local food security. These terror events have driven local farmers to abandon their farms, drained young labor forces out of the crop-producing areas, hampered the transportation of food supplies into Maiduguri, interrupted the businesses at the food markets in Maiduguri, and affected the purchasing power of the local residents (Awodola and Oboshi 2015).

Capability: “Being Physically Safe”

This capability reflects individual levels of well-being in terms of being physically safe. Within the study, an individual’s level of security was determined by using limited survey data pertaining to feeling safe walking down the street at the night (Table A3). Additional information related to an individual’s reasons for daily routes traveled, time of day activities are performed, and limitations in access to water and food would be useful in determining an individual’s capacity of being physically safe.

Table A3. Capability of “Being Physically Safe” (NBS 2009).

Indicator	NBS Question	Answer
Do Household Members Feel Safe Walking on the Street at Night?	Do household members feel safe walking down the street at night?	Not at all safe. Not too safe. Somewhat safe. Very safe.

Indicator: “Do Household Members Feel Safe Walking on the Street at Night?”

Physical safety is both objective and subjective. The subjective physical safety is the individuals’ perception of being free from danger or threat (OED [Oxford English Dictionary] 2015b). This subjective aspect of physical safety can be determined through survey questions about the local residents’ feelings of their physical safety levels. In our study, the indicator of “Do Household Members Feel Safe Walking down the Street at Night?” was used to reflect the subjective aspect of the local residents’ physical safety in Maiduguri, Nigeria. The objective facet of physical safety is referred to as the individuals’ “state of being protected from or guarded against hurt or injury” and “freedom from danger” (OED 2015a). The objective aspect of physical safety can be reflected by indicators such as

crime rate of the local community, and the per capita number of injuries or deaths caused by violent events in the local community. Researchers have not yet found satisfactory indicators reflecting the objective aspect of physical safety for our purpose. It is recognized that the identification of these indicators would increase the accuracy of this study's model results.

In the northern states of Nigeria, especially in Borno State, religious violence committed by the BH religious sect has posed great threat to the well-being of the local residents. In Maiduguri, the BH extremists attack police stations, mosques and churches, and food markets (Onuoha 2010, 60; Awodola and Oboshi 2015, 14). With the rise of such terrorist events, it is also observed that local gunshot injuries have become rampant in Maiduguri (Abba et al. 2012, 19).

Given the existing poor physical safety situation in and around Maiduguri, it is helpful to identify how the local residents perceive their physical safety levels.

Capability: “Being Sheltered”

An individual's housing situation was determined based on limited survey data pertaining to problems paying rent (see Table A4). Additional information related to an individual's access to housing, living conditions, income status, and family dynamics would enhance the understanding of an individual's capacity of being sheltered.

Table A4. Capability of “Being Sheltered” (NBS 2006).

Indicator	NBS Question	Answer
Frequency of Problems Paying House Rent	How often in the last year did you have problems satisfying the house rent of the household?	Never. Seldom. Sometimes. Often. Always.

Indicator: “Frequency of Problems Paying House Rent”

According to the United Nation's “Universal Declaration of Human Rights,” an adequate level of housing is one of the major elements that constitute an adequate standard of living, which has been defined as a universal right of all human beings (UNGA [United Nations General Assembly] 1948, 76). For some researchers, housing is one of the best indicators

of a person's standard of living and her/his place in the society (Festus and Amos 2015, 53).

In Nigeria, with the rapid rate of urbanization, there has been a great shortage of adequate housing facilities in urban areas (Abiodun 1976, 339). A phenomenal increase of housing needs resulting from such shortages in housing units is common, especially in the urban centers (Olotuah and Taiwo 2013, 2).

In order to reflect the local residents' well-being level in terms of the capability of "Being Sheltered," the indicator "Frequency of Problems Paying House Rent" was used. It is assumed that those households in Maiduguri who are having more frequent problems paying house rent tend to have a lower level of quality of life in terms of being sheltered.

Restoring housing is always one of the most important aspects of community recovery (Zhang and Peacock 2010, 5). However, such a housing recovery process is not the same for all affected individuals. Residents with lower socioeconomic status tend to experience disproportionately higher levels of damage (Peacock et al. 2014, 357). The more socially vulnerable population is more prone to experiencing a deterioration of housing condition, even after a disaster recovery process.

Capability: "Having Access to Energy"

This capability reflects the well-being level of individuals living in the study area in terms of having access to the electrical grid (or an alternative power source), and what energy source is actually used and reliable.

Since there are relatively very few respondents who gave the other three answers (shown in Table A5), the answers of "None" and "NEPA (National Electric Power Authority) only" are the only ones taken into account within this study's regression model.

Table A5. Capability of "Having Access to Energy" (NBS 2006).

Indicator	NBS Question	Answer
Source of Electricity	What is the main source of electricity?	None. NEPA only. Rural electrification only. Private generator only. Rural electricity plant or generator.

Indicator	NBS Question	Answer
Number of Hours without Electricity in Previous 24 Hours	How many hours have you experienced without electricity during the previous 24 hours?	0-24

Indicator: “Source of Electricity”

Energy is the most important element in the economic development, poverty eradication, and security of any nation state in the modern world. Its consumption is directly related to the standard of living of the individual residents (Oyedepo 2012, 2).

Although Nigeria has an abundance of energy resources, the country has been experiencing an energy crisis for two decades (Oyedepo 2012, 2-3). In 2009, only about 40% of households in Nigeria were connected to the national grid (Sambo 2009, 15). According to the Nigerian Energy Policy report from 2003, even those connected to the national grid system were short of power supply over 60% of the time (Obadote 2009, 2).

According to the 2006 survey, NEPA was the sole monopoly of power generation, transmission, and distribution in Nigeria since 1972 (Olukotun 2004, 53–54). Rural residents in Nigeria still use biomass energy such as firewood, agricultural residue, animal wastes, municipal solid wastes, sawdust, and wood wastes, as main sources of energy (Sambo 2009, 16–17). Nonetheless, NEPA’s electricity service had been increasingly intolerable according to the local residents (Olukotun 2004, 54). When a community disruption occurs, the local neighborhoods in the affected area will experience a loss of access to electricity (Mileti 1999, 91–92).

Indicator: “Number of Hours without Electricity in the Previous 24 Hours”

This indicator represents the individuals’ capability of having access to a reliable source of electricity, and how the individual’s daily routines are shaped by this access to electricity.

In terms of using the indicator “Number of Hours without Electricity in Previous 24 Hours,” the rationale is that this indicator reflects the quality of electricity service that one household in Nigeria is enjoying. However, when using this indicator, there is a need to be aware that only less than 45% of the respondents provided meaningful answers to this survey ques-

tion. Although this percentage is consistent with the percentage of population that has access to the national grid system, such a small percentage of meaningful answers might pose difficulties to the operations of running this study's regression model.

In spite of these facts, literature shows that when a large scale of disruption occurs to a community, the local residents' access to electricity could be severely impacted (Mileti 1999, 91–92). Thus, it is anticipated that if a local household is already experiencing a large number of hours without electricity in a 24-hour period, a disruption could decrease availability of electricity to a greater extent.

Capability: “Earning Income”

This capability reflects the well-being of individuals living in the study area in terms of income and financial status (see Table A6). It characterizes the household's financial well-being.

Table A6. Capability of “Earning Income” (NBS 2009).

Indicator	NBS Question	Answer
Household Financial Situation	What is your household financial situation?	Very poor. Poor. Moderate. Fairly rich. Rich.

Indicator: “Household Financial Situation”

Adequate income is one of the fundamental aspects that determine the well-being level of an individual (Sen 1993, 41–42; Burchardt 2010). An individual's income level is also highly correlated with her/his other well-being dimensions such as being literate and being healthy (Sen 1999a, 19).

Since 2014, Nigeria has emerged as Africa's largest economy (CIA [Central Intelligence Agency] 2015). Its gross domestic product (GDP) at market prices was US\$568.5 billion in 2014 (World Bank 2016). However, affected by its total population of 177.5 million, Nigeria's GDP per capita was a mere US\$3,203, ranking Nigeria 119 among a total of 184 countries with the available data around the world (World Bank 2016). Also, Nigeria has a gross national income (GNI) per capita of US\$2,970, only the 114th highest among the 171 national entities with available data in the world (World

Bank 2016). Additionally, Nigeria's inflation rate of 8.1% in 2014, as measured by the consumer price index, was the 17th highest among 173 countries in the world (World Bank 2016). The unemployment rate of Nigeria was at 7.5% in 2014, ranking it 76 among 174 countries in the world (World Bank 2016). However, Nigeria's Gini index is relatively large, at 43.0 in 2009, ranking it 22 among the 75 countries with the available data (World Bank 2016). Therefore, the overall income level of an average household in Nigeria is medium low, compared to other countries in the world.

A household's financial situation reflects the level of the household's capability of "Earning Income." Thus, in order to represent the local residents' well-being level in terms of earning income in Maiduguri, "Household Financial Situation" was chosen as an appropriate indicator.

Literature suggests a large scale disruption to a community could severely affect the local residents' assets and livelihoods, both of which could contribute to a change of income to the population in the affected area (Mileti 1999, 98; Wisner et al. 2003, 222). However, such a disruption might unequally affect the local residents' financial situation. The redistribution of income after a community disruption is determined to a large extent by the socioeconomic factors of the local neighborhoods (Wisner et al. 2004, 222).

Capability: "Owning Property"

This capability characterizes the levels of well-being in terms of owning or renting a home and owning household items or durables, as identified in Table A7. In Table A7, the answers "Rents the dwelling," "Pays nominal or subsidized rent," "Uses without paying rent," and "Nomadic or temporary dwelling" were grouped together and then tagged with "Does not own the dwelling." As for owning durables, the potential items that individuals may possess are listed.

Table A7. Capability of “Owning Property” (NBS 2006).

Indicator	NBS Question	Answer
Number of Household Durables	Does your household own an electric iron? Does your household own a charcoal iron? Does your household own a refrigerator? Does your household own a television? Does your household own a personal computer? Does your household own a fixed line telephone? Does your household own a mobile phone? Does your household own a mattress or bed? Does your household own a radio? Does your household own a watch or clock? Does your household own a sewing machine? Does your household own a modern stove? Does your household own gas cooker? Does your household own a generator? Does your household own a bicycle? Does your household own a motorcycle? Does your household own a vehicle? Does your household own a fan? Does your household own a canoe? Does your household own a mat? Does your household own a VCR (videocassette recorder)? Does your household own a donkey? Does your household own a camel? Does your household own furniture?	Yes No
Dwelling Ownership	What is the occupancy status of the dwelling used?	Owns the dwelling. Rents the dwelling. Pays nominal or subsidized rent. Uses without paying rent. Nomadic or temporary dwelling.

Indicator: “Number of Household Durables”

The household durables indicator is a composite index. It is constructed to represent individuals’ capability of “Owning Property” with respect to durable goods. Being able to hold property in the form of durable goods and having the pertinent property rights on an equal basis with others is one of the major aspects of an individual’s central capability of control over their material environment (Nussbaum 2011, 34). Also, the characteristics of

commodities or goods possessed by an individual provide the basic information for deriving that individual's capability (Sen 1999b, 6–7).

In Maiduguri, Nigeria, scholars have utilized ownership of the individual assets as an indicator to demonstrate the positive result of local development program, such as the Promoting Sustainable Agriculture project in southern Borno State (PROSAB [Promoting Sustainable Agriculture Project in Southern Borno State, Nigeria] in Manza and Atala 2014). However, by combining all the variables of durable ownership together, a more vivid picture is captured that manifests the well-being levels of the local households.

When a community disruption occurs, residents living in the affected area are likely to experience losses due to damage to their personal belongings, such as their durable properties (Tobin and Montz 1997, 250; Mileti 1999, 66). It is anticipated that a disruption could reduce the number of durables possessed by one household living in the affected area.

Indicator: “Dwelling Ownership”

Home ownership is traditionally regarded as a major indicator of economic well-being at the household level (Megbolugbe and Linneman 1993, 659). Conventional urban studies researchers note that home ownership increases local residents' opportunity level through enhancing personal wealth, improving local residents' psychological and physical health, supporting youth behaviors that facilitate social advancement, promoting neighborhood stability, and encouraging participation in voluntary activities (Rohe et al. 2002, 53). Although the causal relationship between home ownership and the perceived benefits associated with home ownership still is not well understood (Schwartz 2010, 292), home ownership is correlated with those benefits, and especially noticeably for this study's purpose, home ownership is correlated with personal wealth that facilitates the possession of properties.

In Nigeria, home ownership is one of the highest priorities of most households (Udechukwu 2008, 182). For those who own a house in Nigeria, home ownership “represents their largest singular investment accounting for about 60 percent of household income” (Udechukwu 2008, 182).

Home ownership in Nigeria brings substantial social benefits, as it positively affects “educational achievement, civil participation, health benefits, public assistance, [and] property maintenance and improvement” (Halid

and Akinnitire 2013, 41). Home ownership in Nigeria also provides “pride of ownership, freedom of control, privacy, strong credit base, financial stability, [and appreciation] of asset” (Halid and Akinnitire 2013, 41).

Home ownership in Nigeria is to a large extent determined by income level of the household (Halid and Akinnitire 2013; Nwakanma and Nnamdi 2013). However, as has been indicated by the 8th indicator “Household Financial Situation,” most of the Nigerian residents have a moderate, poor, or very poor level of income. Consequently, Nigeria’s urban owner-occupancy rate was merely 52% in 2008 (EFInA [Enhancing Financial Innovation and Access] 2010, 30). Concomitant to the low income level of local residents, other barriers to home ownership in Nigeria include problems with land accessibility in terms of poor land availability and difficulty in land transaction, a poor mortgage finance system, a high inflation rate, the high cost of building materials, and poor quality of construction (Halid and Akinnitire 2013, 42; Udechukwu 2008, 185–191; Udoekanem et al. 2014, 186).

Capability: “Being Mobile”

This capability characterizes daily routines, destinations, and available modes of transportation of individuals (see Table A8).

Indicator: “Time to Nearest Food Market”

The level of mobility depends on both internal physical ability of an individual to move and the external environmental factors such as availability and accessibility of transportation facilities.

Since its establishment as a regional capital city, Maiduguri has become a commercial center that attracts people from all other Nigerian states and nearby countries (Kyari 2002, 7–8; Awodola and Oboshi 2015, 13). Consequently, transportation issues are always problematic, both between Maiduguri and other cities in Nigeria and within the city of Maiduguri (Oladejo and Tamber 2014, 448; Mukhtar et al. 2015, 14). In order to capture both the internal and external factors that determine an individual’s travel capability in the city of Maiduguri, using “Time to Nearest Food Market” was proposed as the appropriate indicator.

Table A8. Capability of “Being Mobile” (NBS 2006).

Indicator	NBS Question	Answer
Time to Nearest Food Market	How long does it take you to the nearest food market?	0-14 minutes. 15-29 minutes. 30-44 minutes. 45-59 minutes. 60+ minutes.

In Maiduguri, among others there are three major food markets: (1) Gom-boru market for perishable products, (2) the Baga fish market for fish and seafood, and (3) the Monday Market for food distribution and supply inside and outside Nigeria (Awodola and Oboshi 2015, 13). Given that the food markets are located across the city of Maiduguri, “Time to Nearest Food Market” was used as the proxy measure of an individual’s capability of “Being Mobile.”

When a community experiences a severe disruption, the local transportation systems could be severely impacted (Stallings 1995, 117; Mileti 1999, 91). Local residents living in the affected area may find it more difficult to move around. Thus, it is anticipated that after a disruption, the average time that local residents travel to the nearest food market will be increased.

Capability: “Being Educated”

This capability identifies education availability, access, location, and affordability (see Table A9).

Table A9. Capability of “Being Educated” (NBS 2006).

Indicator	NBS Question	Answer
Time to the Nearest Primary School	How long in minutes does it take you from here to reach the nearest primary school?	0-14 minutes. 15-29 minutes. 30-44 minutes. 45-59 minutes. 60+ minutes.
Frequency of Problems Paying School Fees	How often in the last year did you have problems satisfying the school fees needs of the household?	Never. Seldom. Sometimes. Often. Always.

Indicator: “Time to the Nearest Primary School”

In a modern human society, education is a necessity of life (Dewey 1916, 1). According to the United Nations Universal Declaration of Human Rights, everyone “has the right to education” (UNGA 1948, 76). Since 1990, the UNDP has been weighting knowledge and education as one of the pivotal aspects in its HDRs and HDIs for each country (see, e.g., UNDP 1990; 2000; 2010; 2015). Within its HDRs and HDIs, the UNDP uses indicators such as literacy rate, expected years of schooling, and mean years of schooling, without referring to indicators about access to educational infrastructure. However, in our study, the condition of “access to educational infrastructure” also reflects the level of an individual’s well-being in terms of her/his capability of “Being Educated.”

In Nigeria, one of the specific goals of education is to ensure “and sustain unfettered access and equity to education for the total development of the individual” (FME [Federal Ministry of Education] 2013, 2). According to the FME of Nigeria’s annual report for 2013, access to both basic and secondary education in Nigeria continues to improve nationwide recently (FME 2014, 22–23). With the support of the federal government through the Universal Basic Education Commission (UBEC), billions of naira (1 naria is currently equivalent to .0034100 U.S. dollars) have been allocated to enhance the educational infrastructure in Nigeria, in terms of school facilities and staff accommodation, so as to increase and improve equitable access to quality basic education (FME 2014, 23).

In spite of the Federal government’s efforts to provide equitable educational opportunities for all citizens in Nigeria, the rate of women’s participation in education is still low, especially in Maiduguri. According to the local scholarship, the main factors of this gender inequality in access to educational infrastructure include: attitude of parents, traditional practices, socioeconomic status of parents, and the general illiteracy rate in Maiduguri (Okafor 2010). In addition to those factors, the religious extremist movement of the BH has also been posing a threat to access to educational facilities, considering that the group’s name literally means “Western education is forbidden” (Chothia 2012). Given these factors and the fact that, in general, there are more primary schools available than secondary schools, the indicator of “Time to the Nearest Primary School” was selected to reflect the level of access to the local educational infrastructure.

When a disruption occurs to a local community's educational infrastructure, although it is expected that there will be no impact to an individual's well-being level and capability of "Being Educated," it is anticipated that access to educational facilities will be affected.

Indicator: "Frequency of Problems Paying School Fees"

This indicator characterizes the ability to afford schooling when education facilities are available and they are accessible. A high quality of education has the power to: reduce poverty, boost job opportunities, drive economic growth, increase people's chances of leading a healthy life, deepen democratic institutions, protect the environment, assist community to adapt to climate change, and enhance gender equity (UNESCO [United National Educational, Scientific, and Cultural Organization] 2014, 143). In order to "unlock the wider benefits of education, all children need access to both primary and lower secondary education of good quality" (142). One of the key factors that affects the quality of the universal primary and lower secondary education is school fees (UNESCO 2015, 77).

In 1976, the federal government of Nigeria initiated the Universal Primary Education (UPE) scheme, which was abandoned midway (Aluede 2006, 97). The most recent effort for promoting primary education is the Universal Basic Education (UBE) program, which was launched by President Olusegun Obasanjo's administration in 1999 (97). The UBE program intends to provide a nine-year universal, free, and compulsory education for children, with six years of primary schooling plus three years of junior secondary school education (Tsafe 2013, 24–25).

Educational funding "to meet maintenance or running costs, or to obtain supplies of instructional materials and other educational inputs" used to be a problem for educational provision in Nigeria (World Bank 1998, xiii). But since the initiation of the UBE program, access to basic education in Nigeria has been greatly improved. These improvements include: enrolment in primary schools, gender parity, retention and completion in primary schools, and transition from primary schools to secondary schools (FME 2014, 22). In 2013, the total amount allocated to basic education in Nigeria was 38.5 billion naira (\$131.29 million U.S. dollars); the average amount between 2005 and 2013 was 27.6 billion naira (FME 2014, 65).

Capability: “Having Access to Medical Services”

This capability characterizes access, availability, location, and affordability of medical services by individuals (see Table A10).

Table A10. Capability of “Having Access to Medical Services” (NBS 2006).

Indicator	NBS Question	Answer
Time to the Nearest Hospital	How long in minutes does it take from here to reach the nearest health clinic or hospital?	0-14 minutes. 15-29 minutes. 30-44 minutes. 45-59 minutes. 60+ minutes.
Frequency of Problems Paying for Healthcare	How often in the last year did you have problems stratifying the healthcare needs of the household?	Never. Seldom. Sometimes. Often. Always.

Indicator: “Time to the Nearest Hospital”

Having access to medical services allows individuals the opportunity to receive healthcare which reflects a high level of well-being. Access to medical services is “the opportunity to reach and obtain appropriate health care services in situations of perceived need for care” (Levesque et al. 2013, 21). Its quality depends on “the interface between the characteristics of persons, households, social and physical environments and the characteristics of health systems, organisations and providers” (Levesque et al. 2013, 21). The study reported here noted that access to medical services has two facets. One is the physical access, which refers to whether an individual can physically reach a healthcare facility. The other facet is the social access, which is related to the affordability of the medical services.

Travel time to healthcare facility is one of the key indicators used to measure the organization of medical services and the characteristics of the population at risk (Aday and Andersen 1974, 217). On the one hand, for rural areas, a 30-minute travel time standard to general hospitals has long been applied in the well-developed countries to determine the geographic accessibility of medical services (Bosanac et al. 1976). On the other hand, researchers have found that travel time to a medical facility is a pivotal factor that influences hospital choice, even in urban areas where alternative op-

tions are widely available (McGuirk and Porell 1984). More recently, researchers also used travel time to a health care facility to define rational hospital catchment areas (Schuurman et al. 2006) and to reflect the effect of centralization of health care services (Kobayashi et al. 2015).

Although the healthcare system in Nigeria is generally weak in delivering medical services (FMH [Federal Ministry of Health] 2010, 32), there are a number of medical facilities that provide medical and health services to the local residents in Maiduguri. The major medical clinics and hospitals in Maiduguri include: the University of Maiduguri Teaching Hospital, the State Specialist Hospital, the New Foundation Hospital, the Federal Neuro-Psychiatric Hospital, the Sunni Hospital, the Kanem Hospital, the Avon Healthcare Nakowa Specialist Hospital, the Old Maiduguri Clinic, the Maiduguri Clinic, the Clinic, the Muhammad Buba Marwa House, the Bulabulin Dispensary, the Deribe Hospital, the Alheri Hospital, the Abbaganaram Clinic, and others (Hospitalby 2016). These medical facilities are located across the urban area that is north of the Ngadda and Gambole Rivers.

When a large-scale disruption occurs, it could severely damage the local transportation systems (Mileti 1999, 91). Especially when bridges are no longer functional and the road network is compromised, traveling to the hospital becomes problematic.

Indicator: “Frequency of Problems Paying for Healthcare”

Having access to medical services encompasses the availability, access, and affordability of healthcare. The indicator “Frequency of Problems Paying for Health Care” is used to determine the level of care received.

Health care, or medical service, is one of the major social services that a society can provide to enhance individuals' capabilities (Ariana and Naveed 2009, 233). However, there can be several barriers to the utilization of health care services. Among these barriers, price and cost factors are the most prevalent—on both the demand and the supply sides. These price and cost factors include: (1) indirect consumer costs such as distance cost and opportunity cost; (2) price and availability of substitute health products and services; (3) direct price of service of a given level of health service quality, including informal payment; and (4) price of drugs and other consumables (Ensor and Cooper 2004, 70). Given the importance of the price and cost factors in determining the capability level of “Having

Access to Medical Services,” “Frequency of Problems Paying for Health Care” was selected as the appropriate indicator reflecting the capability of “Having Access to Medical Services.”

In Nigeria, the public health condition is poor. Its overall health system performance was ranked only 187th among the 191 member states of the WHO in 2000. Nigeria’s maternal mortality rate is one of the highest in the world (FMH 2006a, 3). According to the FMH of Nigeria, despite “considerable investment in the health sector over the years, available evidence suggests that health services throughout Nigeria are delivered through a weak health care system” (FMH 2010, 32). Nigeria’s “health care system is unable to provide basic, cost-effective services for the prevention and management of common health problems especially at the LGA and Ward levels” (FMH 2010, 33). In addition, the majority of Nigerians (90.2%) who live below the income level of \$2 a day are unable to afford and obtain medication in Nigeria (FMH 2006b, 5).

When a severe disruption occurs, it could cause fatalities and injuries as well as psychological impacts to the local population (Lindell and Prater 2003, 177–178). Given the existing poor condition of public health service in Nigeria, it is anticipated that a massive disruption in Maiduguri will severely increase the demand for local medical service. Such a sharp increase in demand for medical service will lead to greater barriers to the local access to medical service.

Capability: “Being Socially Connected”

An individual’s level of social connectivity was only able to be determined by using limited survey data pertaining to religious association (see Table A11). Additional information pertaining to an individual’s daily routines, practices, form of communication, access to information, family dynamics, and living conditions would be useful in characterizing an individual’s capability of social connectivity.

Table A11. Capability of “Being Socially Connected” (NBS 2009).

Indicator	NBS Question	Answer
Can Household Depend on Religious Association during Difficult Period?	Can household depend on religious association during difficult period?	Yes. No.

Indicator: “Can Household Depend on Religious Association during Difficult Period?”

Being socially connected is equivalent to the central human capability of affiliation, which means an individual is “able to live with and toward others, to recognize and show concern for other human beings, to engage in various forms of social interaction, [and] to be able to imagine the situation of another” (Nussbaum 2007, 23). Being socially connected also means the possession of social capital, which refers to the “connections among individuals—social networks and the norms of reciprocity and trustworthiness that arise from them” (Putnam 2000, 19). Social capital is virtually most powerful when it is “embedded in a dense network of reciprocal social relations” (Putnam 2000, 19). From the perspective of disaster management, social capital is the “potential resources in goods, labor, and other forms of assistance, that are embedded in local-level social networks of family and neighbors, and other groups formed through place-based, work-based, and common interest-based bonds of interaction, trust, reciprocity, and support, that people can mobilize individually and collectively to use for community resilience in the face of disasters” (LaLone 2012, 211).

According to political scientist Daniel Aldrich, high levels of social capital serve as the core engine of disaster recovery (2012, 15). In general, strong social capital provides information, knowledge, and access to members of the network; strong social ties create trust among network members; and social capital builds new norms about compliance and participation (Aldrich 2012, 46). As has also been pointed out by Aldrich, however, social capital can be a double-edged sword in a disaster situation. When overlaid with prejudice and discrimination, “strong social relationships across certain groups can slow down the recovery of out-groups” (Aldrich 2012, 14). Further, “peripheral or marginalized groups within society that hold less social capital benefit little and often are harmed by the groups holding stronger social capital after a disaster” (Aldrich 2012, 14). Those who hold the power always have a tendency to relentlessly “search for scapegoats to blame for destruction and loss of life” (Drabek and Quarantelli 1968, 12; see Farley 2000, 25 for scapegoating and projection).

Within social capital, religious involvement is one of the principal components of civic engagement (Putnam 2000, 69). According to political scientist Robert Putnam, “[regular] worshipers and people who say that religion is very important to them are much more likely than other people to visit

friends, to entertain at home, to attend club meetings, and to belong to sports groups; professional and academic societies; school service groups; youth groups; service clubs; hobby or garden clubs; literary, art, discussion, and study groups; school fraternities and sororities; farm organizations; political clubs; nationality groups; and other miscellaneous groups” (Putnam 2000, 66–67). Religious involvement is also a strong predictor of volunteerism and philanthropy (Putnam 2000, 66–67).

Appendix B: Probabilistic Predictive Models of Indicator Indices

After selecting the capability indicators, the proposed formulation in Chapter 3 was used to develop probabilistic predictive models of the indicator indices. To calibrate the predictive models and estimate their unknown model parameters, the available survey database was used for Maiduguri, Nigeria.

Capability: “Meeting the Physiological Needs”

The capability of “Meeting the Physiological Needs” consists of three indicators to quantify the achieved functionings. The selected indicators are: (1) “Main Source of Drinking Water;” (2) “Frequency of Problems with Supply of Drinking Water;” and (3) “Frequency of Problems with Satisfying Food Needs.” The first indicator is tracked in the aftermath of the disruptive event by means the infrastructure network analysis. To predict the categories of the other two indicators, probabilistic predictive models were developed, as explained in Chapter 3.

Table B1 shows the codebook of the three possible outcomes of the indicator “Frequency of Problems with Supply of Drinking Water.” Because the indicator is of the categorical type, Equation (3) is used to develop the predictive model. For this purpose, a list of candidate regressors is first selected that can influence the possible outcome of the indicator. Table B2 summarizes the list of candidate regressors considered for developing the predictive model. The stepwise deletion process was used to assess the statistical significance of the candidate regressors. After the elimination of statistically insignificant terms, the deletion process is stopped and two regressors, $x_{2,6}$ and $x_{2,9}$, are left in the model. The final form of the predictive model is shown in Equation (31):

$$\mathbf{P}[I_2(\mathbf{x}_2, \Theta_2) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{6,9\}} \theta_{2,k,j} x_{2,j}\right)}{1 + \sum_{k=1}^2 \exp\left(\sum_{j \in \{6,9\}} \theta_{2,k,j} x_{2,j}\right)}, & k \in \{1, 2\}, \\ \frac{1}{1 + \sum_{k=1}^2 \exp\left(\sum_{j \in \{6,9\}} \theta_{2,k,j} x_{2,j}\right)}, & k \in \{3\}. \end{cases} \quad (31)$$

Table B1. Codebook of the indicator $I_2 :=$ “Frequency of Problems with Supply of Drinking Water.”

Category	Codebook	Percentage of Population
No	1	54.4
Dry season	2	43.7
Frequently	3	1.9

Table B2. List of candidate regressors for the predictive model of I_2 .

Regressor
$x_{2,1} :=$ Constant
$x_{2,2} :=$ Age of the household head
$x_{2,3} :=$ Household size
$x_{2,4} :=$ Occupational group of the household head
$x_{2,5} :=$ Educational status of the household head
$x_{2,6} :=$ Road construction projects in the last 5 years
$x_{2,7} :=$ Time to the nearest food market
$x_{2,8} :=$ Time to the nearest hospital
$x_{2,9} :=$ Main source of drinking water
$x_{2,10} :=$ Provider of drinking water

Table B3 summarizes the posterior statistics of the parameters. The relation between the indicator and both of the selected regressors is of the causal kind. The regressors, $x_{2,6}$ and $x_{2,9}$, are explaining the two common causes of problem with the supply of drinking water. The regressor $x_{2,6}$ implies that the ease of access to the source of drinking water could be a cause of a problem with the supply of drinking water. Specifically, when the main source of drinking water is “pipe borne” or “vendor, truck” a decisive factor is the ease of transportation, which depends on the existence of the paved roads among other factors. Furthermore, the “Main Source Of Drinking Water,” captured by $x_{2,9}$, is another cause of the problem. The source of drinking water influences both its quality and availability. For instance, “pipe borne” and “vendor, truck” are considered to be better sources with respect to pond or river water, in terms of both quality and availability, particularly during the dry season.

Table B3. Posterior statistics of the parameters in the predictive model of I_2 .

Parameter	Mean	Standard Deviation
$\theta_{2,1,6}$	5.32	1.31
$\theta_{2,1,9}$	-2.90	0.82
$\theta_{2,2,6}$	2.36	1.24
$\theta_{2,2,9}$	-0.06	0.68

Next, similar steps were followed to develop a probabilistic predictive model for the indicator “Frequency of Problems with Supply of Drinking Water.” Table B4 shows the corresponding codebook. This indicator is also of the categorical type; hence, Equation (3) was used to develop the predictive model. Table B5 summarizes the candidate regressors. Using the stepwise deletion process arrives at a parsimonious, yet accurate form of the model, shown as Equation (32):

$$\mathbf{P}\left[I_3(\mathbf{x}_3, \Theta_3) = k\right] = \begin{cases} \frac{\exp\left(\sum_{j \in \{10,11,13\}} \theta_{3,k,j} x_{3,j}\right)}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{10,11,13\}} \theta_{3,k,j} x_{3,j}\right)}, & k \in \{1, 2, 3\}, \\ \frac{1}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{10,11,13\}} \theta_{3,k,j} x_{3,j}\right)}, & k \in \{4\}. \end{cases} \quad (32)$$

Table B4. Codebook of the indicator I_3 := “Frequency of Problems Satisfying Food Needs.”

Category	Codebook	Percentage of Population
Never	1	17.2
Seldom	2	18.5
Sometimes	3	44.4
Often	4	19.9

Table B5. List of candidate regressors for the predictive model of I_3 .

Regressor
$x_{3,1}$:= Constant
$x_{3,2}$:= Age of the household head
$x_{3,3}$:= Household size
$x_{3,4}$:= Marital status of the household head
$x_{3,5}$:= Occupational group of the household head
$x_{3,6}$:= Educational status of the household head
$x_{3,7}$:= Number of members contributing to income
$x_{3,8}$:= Road construction projects in the last 5 years
$x_{3,9}$:= Time to the nearest school
$x_{3,10}$:= Time to the nearest food market
$x_{3,11}$:= Welfare quintile

Regressor
$x_{3,12} :=$ Dwelling ownership
$x_{3,13} :=$ Frequency of problems with supply of drinking water

Table B6 summarizes the posterior statistics of the parameters. The regressors left in the final form of the model are $x_{3,10}$, $x_{3,11}$, and $x_{3,13}$. The regressors $x_{3,10}$ and $x_{3,13}$ are of the causal kind, and they explain two common causes of having problem with satisfying food needs. The regressor $x_{3,10}$ is related to the ease of access to the food market, and regressor $x_{3,13}$ is related to the household's purchasing power. Though regressor $x_{3,11}$ could marginally cause problems with satisfying food needs (e.g., through the required water to prepare food), it could generally be considered of the noncausal kind. The interpretation of the noncausal relation is that the households facing problems with supply of drinking water are generally expected to have problems with satisfying food needs as well.

Table B6. Posterior statistics of the parameters in the predictive model of I_3 .

Parameter	Mean	Standard Deviation
$\theta_{3,1,10}$	2.11	0.40
$\theta_{3,1,11}$	1.83	0.39
$\theta_{3,1,13}$	-5.95	1.00
$\theta_{3,2,10}$	0.27	0.43
$\theta_{3,2,11}$	1.31	0.32
$\theta_{3,2,13}$	-2.35	0.62
$\theta_{3,3,10}$	1.08	0.33
$\theta_{3,3,11}$	1.00	0.29
$\theta_{3,3,13}$	-2.00	0.52

Capability: “Being Physically Safe”

To quantify the achieved functioning in the capability of “Being Physically Safe,” the subjective indicator “Do Members Feel Safe Walking on the Street at Night?” was used as the sole indicator. Ideally, it would be desirable to have an objective indicator (besides the subjective one) that shows the number of crime-like robberies committed in the community. However, the objective indicators in the survey database lack enough variation to be quantified by means of the predictive models (i.e., more than 97% of the interviewed individuals reported they have never been subjected to any crime). Regarding this capability, it is important to know how safe individuals feel in their communities, beyond the actual collected data of the committed crime. Such subjective information is particularly relevant when evaluating the capabilities of individuals who have not been significantly impacted by a disruptive event, but are living among others who are suffering from low capabilities.

Table B7 shows the codebook of the indicator. Because the indicator is of the categorical type, Equation (3) was used to develop the predictive model.

Table B8 shows the list of selected candidate regressors to develop the predictive model. Using a stepwise deletion process and eliminating statistically insignificant terms, the final form of the model is shown as Equation (33):

$$\mathbf{P}[I_4(\mathbf{x}_4, \Theta_4) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{1,9,10,13\}} \theta_{4,k,j} x_{4,j}\right)}{1 + \sum_{k=1}^2 \exp\left(\sum_{j \in \{1,9,10,13\}} \theta_{4,k,j} x_{4,j}\right)}, & k \in \{1, 2\}, \\ \frac{1}{1 + \sum_{k=1}^2 \exp\left(\sum_{j \in \{1,9,10,13\}} \theta_{4,k,j} x_{4,j}\right)}, & k \in \{3\}. \end{cases} \quad (33)$$

Table B7. Codebook of the indicator I_4 := “Do Members Feel Safe Walking on the Street at Night?”

Category	Codebook	Percentage of Population
Very safe	1	47.5
Somewhat safe	2	29.4

Category	Codebook	Percentage of Population
Not too safe	3	23.1

Table B8. List of candidate regressors for the predictive model of I_4 .

Regressor
$x_{4,1} :=$ Constant
$x_{4,2} :=$ Sex
$x_{4,3} :=$ Age
$x_{4,4} :=$ Marital status
$x_{4,5} :=$ Radio, frequency of use
$x_{4,6} :=$ Daily newspaper, frequency of use
$x_{4,7} :=$ Highest grade completed
$x_{4,8} :=$ Standards of living with respect to others in the community
$x_{4,9} :=$ Welfare quintile
$x_{4,10} :=$ Time to the nearest school
$x_{4,11} :=$ Time to the nearest hospital
$x_{4,12} :=$ Time to the nearest food market
$x_{4,13} :=$ Neighborhood watching in the community

Table B9 summarizes the posterior statistics of the model parameters. The remaining regressors in the model are $x_{4,1}$, $x_{4,9}$, $x_{4,10}$, and $x_{4,13}$. The regressor $x_{4,1}$ is a constant, $x_{4,9}$ and $x_{4,10}$ are generally of the noncausal kind, and $x_{4,13}$ is of the causal kind. The noncausal regressors are showing a relation that is typically valid under the calibration condition. For instance, living close to or far away from the nearest school might not necessarily cause a person to feel that a community is safe or unsafe. However, the collected information from the respondents in the survey shows that the feeling of safety and the time to the nearest school are related. Furthermore, the causal regressor, $x_{4,13}$, shows that community members generally feel safe

when they know there is a neighborhood watching that can protect them. It is worth noting that there is a hidden fact in the previous conclusion that conditions the causal relation to the degree of trust in authority.

Table B9. Posterior statistics of the parameters in the predictive model of I_4 .

Parameter	Mean	Standard Deviation
$\theta_{4,1,1}$	-5.23	0.74
$\theta_{4,1,9}$	0.76	0.21
$\theta_{4,1,10}$	1.12	0.24
$\theta_{4,1,13}$	1.63	0.28
$\theta_{4,2,1}$	-2.89	0.67
$\theta_{4,2,9}$	-0.19	0.20
$\theta_{4,2,10}$	1.31	0.24
$\theta_{4,2,13}$	1.19	0.28

Capability: “Being Sheltered”

The achieved functioning in this capability is quantified by means of the indicator “Frequency of Problems with Paying Rent.” In addition to this indicator, three other indicators were considered that are related to the type of material used in the roof, walls, and floor of the dwellings. These indicators were intended to quantify the quality of the dwellings. However, the recorded data in the survey showed there is not enough variation to be quantified by the predictive models. For example, the roof of 94% of dwellings in the database is made of iron sheet. A similar observation also applies to the other two indicators.

Table B10 shows the codebook of the selected indicator. Because the indicator is categorical, Equation (3) was used to develop the predictive model. Similar to the previous predictive models, a list of candidate regressors was selected that can influence the possible category of the indicator. Table B11 summarizes the list of selected candidate regressors, along with their possible values/categories. After performing the stepwise deletion process and eliminating the statistically insignificant terms, the final form of the model was obtained as Equation (34):

$$\mathbf{P}[I_5(\mathbf{x}_5, \Theta_5) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{2,3,5,6,9,11\}} \theta_{5,k,j} x_{5,j}\right)}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{2,3,5,6,9,11\}} \theta_{5,k,j} x_{5,j}\right)}, & k \in \{1, 2, 3\}, \\ \frac{1}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{2,3,5,6,9,11\}} \theta_{5,k,j} x_{5,j}\right)}, & k \in \{4\}. \end{cases} \quad (34)$$

Table B10. Codebook of the indicator $I_5 :=$ “Frequency of Problems Paying House Rent.”

Category	Codebook	Percentage of Population
Never	1	60.3
Seldom	2	12.6
Sometimes	3	19.9
Often	4	7.3

Table B11. List of candidate regressors for the predictive model of I_5 .

Regressor
$x_{5,1} :=$ Constant
$x_{5,2} :=$ Age of the household head
$x_{5,3} :=$ Household size
$x_{5,4} :=$ Marital status of the household head
$x_{5,5} :=$ Occupational group of the household head
$x_{5,6} :=$ Education level of the household head
$x_{5,7} :=$ Number of members contributing to income
$x_{5,8} :=$ Road construction project in the last 5 years
$x_{5,9} :=$ Time to the nearest food market
$x_{5,10} :=$ Main source of drinking water
$x_{5,11} :=$ Welfare quintile

Table B12 shows the estimated posterior statistics of the model parameters. The regressors remained in the final form of the model are $x_{5,2}$, $x_{5,3}$, $x_{5,5}$, $x_{5,6}$, $x_{5,9}$, and $x_{5,11}$. The higher number of regressors left in the model implies that the selected candidate regressors are not as efficient as in the case of other predictive models in describing the variability in the indicator over the population. More informative regressors might be thought of to improve the model; however, important constraints in developing such predicative models is the availability of the data to calibrate the model and also the ability to measure/predict the values of the regressors at different locations and over time. In this model, the relation of all the regressors can be considered causal, in some sense; however, in general, they do not immediately impact the possible outcome of the indicator. All the regressors, in some sense, are capturing the financial aspect of the problem to pay the rent. For example, the age of the household head and his/her ability to produce wealth are related. Likewise, when the size of the household is large and there is only one or two members contributing to the income, this could be a cause to have a problem with paying the rent. In contrast, when all the members are contributing, this could be seen as a positive effect. The education and occupation of the household head are also contributing to the problem of paying the rent. Specifically, when the occupation is looked at as a binary variable (i.e., employed or unemployed), its causal relation would be more tangible. Among the regressors in Equation (32), distinguishing the causal relation of $x_{5,11}$ is easier, as it is directly related to the economic situation of the household.

Table B12. Posterior statistics of the parameters in the predictive model of I_5 .

Parameter	Mean	Standard Deviation
$\theta_{5,1,2}$	0.14	0.05
$\theta_{5,1,3}$	0.11	0.31
$\theta_{5,1,5}$	-0.70	0.23
$\theta_{5,1,6}$	-0.94	0.26
$\theta_{5,1,9}$	-0.04	0.47
$\theta_{5,1,11}$	1.15	0.61
$\theta_{5,2,2}$	0.10	0.06
$\theta_{5,2,3}$	0.09	0.32

Parameter	Mean	Standard Deviation
$\theta_{5,2,5}$	-0.44	0.25
$\theta_{5,2,6}$	-0.66	0.26
$\theta_{5,2,9}$	-0.81	0.62
$\theta_{5,2,11}$	0.92	0.64
$\theta_{5,3,2}$	0.03	0.06
$\theta_{5,3,3}$	0.76	0.33
$\theta_{5,3,5}$	-0.05	0.27
$\theta_{5,3,6}$	-0.57	0.27
$\theta_{5,3,9}$	0.74	0.48
$\theta_{5,3,11}$	-0.94	0.71

Capability: “Having Access to Energy”

Two indicators were used to quantify the achieved functioning in this capability. The selected indicators are the “Source of Electricity” and the “Number of Hours without Electricity in the Past 24 Hours.” The first indicator determines whether or not households are having access to electricity. The second indicator quantifies the quality of access.

Table B13 shows the codebook of the two possible outcomes of the indicator “Source of Electricity.” NEPA is the main source of electricity in the urban area of Maiduguri, which is the focus of this study. However, in the rural areas, households are using other sources such as private generators or rural electricity plants. Because the indicator is of the categorical type, with two possible outcomes, Equation (3) was used to develop the predictive model. Table B14 summarizes the list of candidate regressors to develop the predictive model. Using the stepwise deletion process, the statistically significant terms were eliminated. The final form of the model consists of regressors $x_{6,6}$, $x_{6,12}$, and $x_{6,14}$, as shown in Equation (35):

$$\mathbf{P}[I_6(\mathbf{x}_6, \Theta_6) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{6,12,14\}} \theta_{6,k,j} x_{6,j}\right)}{1 + \exp\left(\sum_{j \in \{6,12,14\}} \theta_{6,k,j} x_{6,j}\right)}, & k \in \{1\}, \\ \frac{1}{1 + \exp\left(\sum_{j \in \{6,12,14\}} \theta_{6,k,j} x_{6,j}\right)}, & k \in \{2\}. \end{cases} \quad (35)$$

Table B13. Codebook of the indicator I_6 := “Source of Electricity.”

Category	Codebook	Percentage of Population
None	1	12.5
NEPA	2	87.5

Table B14. List of candidate regressors for the predictive model of I_6 .

Regressor
$x_{6,1}$:= Constant
$x_{6,2}$:= Gender of the household head
$x_{6,3}$:= Age of the household head
$x_{6,4}$:= Household size
$x_{6,5}$:= Marital status of the household head
$x_{6,6}$:= Occupational group of the household head
$x_{6,7}$:= Education level of the household head
$x_{6,8}$:= Does the household own a vehicle
$x_{6,9}$:= Time to the nearest school
$x_{6,10}$:= Time to the nearest hospital
$x_{6,11}$:= Time to the nearest food market
$x_{6,12}$:= Welfare quintile

Regressor
$x_{6,13} :=$ Frequency of problems with supply of drinking water
$x_{6,14} :=$ Frequency of problems paying house rent

Table B15 summarizes the posterior statistics of the model parameters. The regressors that remained in the final form of the model are trying to capture the financial aspect of the problem (i.e., whether or not the households can pay the utility bills). Beyond being able or not to pay the bills, the regressors collectively might describe a situation that there is no NEPA coverage in the community. Under both circumstances, the relation of all the regressors could be considered causal but not with immediate impact. Generally speaking, it becomes a matter of time to see the actual impact on the possible outcome of the indicator.

Table B15. Posterior statistics of the parameters in the predictive model of I_6 .

Parameter	Mean	Standard Deviation
$\theta_{6,1,6}$	0.64	0.21
$\theta_{6,1,12}$	-1.56	0.36
$\theta_{6,1,14}$	-1.12	0.46

Next, a probabilistic predictive model was developed for the indicator “Number of Hours without Electricity in the Past 24 Hours.” The possible values are in the interval [0,24], and Table B16 gives a summary of the distribution of the indicator over the considered households for the purpose of calibration. This indicator is of the integer/real-value type; hence, Equation (2) was used to develop the predictive model.

Table B17 summarizes the candidate regressors used to develop the model. The statistically insignificant terms were eliminated from the model, using the stepwise deletion process. The obtained final form of the model is shown as Equation (36):

$$\ln \left[\frac{H_7(\mathbf{x}_7, \Theta_7)}{1 - H_7(\mathbf{x}_7, \Theta_7)} \right] = \sum_{j \in \{1, 13, 14\}} \theta_{7,j} x_{7,j} + \sigma_7 \varepsilon_7, \quad (36)$$

where $H_7(\mathbf{x}_7, \Theta_7) = [I_7(\mathbf{x}_7, \Theta_7) - I_{7,\min}] / (I_{7,\max} - I_{7,\min})$, in which the goalposts are $I_{7,\min} = 0$ and $I_{7,\max} = 24$.

Table B16. Summary of the indicator I_7 := “Number of Hours without Electricity in the past 24 hours.”

Outcome	Percentage of Population
0-2	3.8
3-4	9.2
5-6	5.3
7-8	0.8
9-10	19.8
11-12	35.9
13-14	6.1
15-16	4.6
17-18	9.2
19-20	5.3
21-22	0.0
23-24	0.0

Table B17. List of candidate regressors for the predictive model of I_7 .

Regressor
$x_{7,1}$:= Constant
$x_{7,2}$:= Gender of the household head
$x_{7,3}$:= Age of the household head
$x_{7,4}$:= Household size
$x_{7,5}$:= Marital status of the household head
$x_{7,6}$:= Occupational group of the household head

Regressor
$x_{7,7} :=$ Education level of the household head
$x_{7,8} :=$ Does the household own a vehicle
$x_{7,9} :=$ Time to the nearest school
$x_{7,10} :=$ Time to the nearest hospital
$x_{7,11} :=$ Time to the nearest food market
$x_{7,12} :=$ Welfare quintile
$x_{7,13} :=$ Frequency of problems with supply of drinking water
$x_{7,14} :=$ Frequency of problems paying house rent

Table B18 summarizes the posterior statistics of the model parameters. The regressors left in the final form of the model are $x_{7,1}$, $x_{7,13}$, and $x_{7,14}$. The regressors $x_{7,13}$ and $x_{7,14}$ are both of the noncausal type and explain the general relation between the number of hours having access to electricity and the problems with the supply of drinking water and paying house rent. Alternatively, the access to electricity and the quality of access can be predicted by using a power network analysis, given that the required information is available to perform such an analysis.

Table B18. Posterior statistics of the parameters in the predictive model of l_7 .

Parameter	Mean	Standard Deviation
$\theta_{7,1}$	-2.83	0.40
$\theta_{7,13}$	1.26	0.20
$\theta_{7,14}$	0.44	0.13
σ_7	0.86	0.05

Capability: “Earning Income”

Ideally, it is desirable to use the actual salary of the households as the indicator of the capability “Earning Income.” However, in the absence of such information in the survey database, the self-reported indicator “Household

Financial Situation" was used. Though there might be bias in the self-reported income status, it would be expected that the predictive model would not be adversely affected given that the unknown subset of biased observations is not dominating in the database.

Table B19 shows the codebook of the indicator along with the percentage of population within each category. Because the indicator is categorical, Equation (3) was used to develop the predictive model.

Table B20 lists the set of selected candidate regressors to develop the predictive model. Starting with the complete model (i.e., all candidate regressors), the stepwise deletion process was used to eliminate one term at a time until arriving at a parsimonious form of the model. After elimination of statistically insignificant terms, the final form of the model is obtained as Equation (37):

$$\mathbf{P}[I_8(\mathbf{x}_8, \Theta_8) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{1,3,5\}} \theta_{8,k,j} x_{8,j}\right)}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{1,3,5\}} \theta_{8,k,j} x_{8,j}\right)}, & k \in \{1, 2, 3\}, \\ \frac{1}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{1,3,5\}} \theta_{8,k,j} x_{8,j}\right)}, & k \in \{4\}. \end{cases} \quad (37)$$

Table B19. Codebook of the indicator I_8 := "Household Financial Situation."

Category	Codebook	Percentage of Population
Very poor	1	11.6
Poor	2	29.1
Moderate	3	53.3
Fairly rich	4	6.1

Table B20. List of candidate regressors for the predictive model of I_8 .

Regressor
$x_{8,1} :=$ Constant
$x_{8,2} :=$ Time to the nearest school

Regressor
$x_{8,3} :=$ Time to the nearest hospital
$x_{8,4} :=$ Time to the nearest food market
$x_{8,5} :=$ Does a household member belong to a religious association
$x_{8,6} :=$ Minimum needed per month to satisfy basic needs

Table B21 summarizes the estimated posterior statistics of the model parameters. All the regressors in the final form of the model, $x_{5,1}$, $x_{5,3}$, and $x_{5,5}$, are of the noncausal type. Hence, it is suggested to not change the values of the regressors when predicting the capabilities of households in the immediate aftermath of a disruption.

Table B21. Posterior statistics of the parameters in the predictive model of I_8 .

Parameter	Mean	Standard Deviation
$\theta_{8,1,1}$	1.93	1.47
$\theta_{8,1,3}$	0.51	0.20
$\theta_{8,1,5}$	-1.43	0.75
$\theta_{8,2,1}$	5.79	1.38
$\theta_{8,2,3}$	0.30	0.20
$\theta_{8,2,5}$	-2.93	0.70
$\theta_{8,3,1}$	6.53	1.36
$\theta_{8,3,3}$	0.23	0.19
$\theta_{8,3,5}$	-2.89	0.69

Capability: “Owning Property”

The achieved functioning in this capability is quantified in terms of two indicators. The selected indicators are the “Number of Household Durables” and “Dwelling Ownership.” In selecting the indicators, care should be taken to consider the population under study. Because what constitutes properties for households in rural areas might not be applicable for people

living in urban areas, and vice versa. For example, the area of land, or the number of animals like sheep, goats, and cows are considered to be properties for households living in rural areas, which is not the case for people in urban areas.

Table B22 shows the codebook of the possible outcomes of the indicator “Number of Household Durables.” The table also shows the items considered as properties for households in the urban area of Maiduguri, as the focus of this study. Because the indicator is categorical, Equation (3) was used to develop the predictive model.

Table B23 lists the set of candidate regressors for developing the predictive model. A stepwise deletion process was used to eliminate the statistically insignificant terms. The final form of the model is shown in Equation (38):

$$\mathbf{P}[I_9(\mathbf{x}_9, \Theta_9) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{1,2,11,12\}} \theta_{9,k,j} x_{9,j}\right)}{1 + \sum_{k=1}^4 \exp\left(\sum_{j \in \{1,2,11,12\}} \theta_{9,k,j} x_{9,j}\right)}, & k \in \{1, \dots, 4\}, \\ \frac{1}{1 + \sum_{k=1}^4 \exp\left(\sum_{j \in \{1,2,11,12\}} \theta_{9,k,j} x_{9,j}\right)}, & k \in \{5\}. \end{cases} \quad (38)$$

Table B22. Summary of the indicator I_9 := “Number of Household Durables” (including refrigerator, television, personal computer, fixed-line telephone, mobile phone, modern stove, gas cooker, generator, bicycle, motorcycle, vehicle).

Outcome	Percentage of Population
0	25.5
1	21.7
2	18.0
3	11.2
4	7.5
5	8.1
6	7.5

Table B23. List of candidate regressors for the predictive model of I_9

Regressor
$x_{9,1} :=$ Constant
$x_{9,2} :=$ Age of the household head
$x_{9,3} :=$ Household size
$x_{9,4} :=$ Marital status of the household head
$x_{9,5} :=$ Occupational group of the household head
$x_{9,6} :=$ Education level of the household head
$x_{9,7} :=$ Number of members contributing to household income
$x_{9,8} :=$ Road construction project in the last five years
$x_{9,9} :=$ Time to the nearest hospital
$x_{9,10} :=$ Time to the nearest food market
$x_{9,11} :=$ Main source of drinking water
$x_{9,12} :=$ Welfare quintile

Table B24 summarizes the posterior statistics of the model parameters. The regressors that remained in the final form of the model— $x_{9,1}$, $x_{9,2}$, $x_{9,11}$, and $x_{9,12}$ —are generally of noncausal type. Only $x_{9,12}$ might be considered as causal. The regressors partially explain the reasoning behind having the selected durables, given that such an opportunity is available. Hence, it is suggested not to update the categories of regressors, such as the “Main Source of Drinking Water,” when predicting the outcome of the indicator in the immediate aftermath of a disruption.

Next, a probabilistic predictive model was developed for the indicator “Dwelling Ownership.” The possible values are either owning or renting a house. Table B25 shows the codebook of the indicator, along with the percentage of considered households within each group. Because the indicator is categorical, Equation (3) was used to develop the predictive model.

Table B26 summarizes the candidate regressors used to develop the model. The statistically insignificant terms are eliminated from the model, using the stepwise deletion process. The final form of the model is shown as Equation (39):

$$\mathbf{P}[I_{10}(\mathbf{x}_{10}, \Theta_{10}) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{5,9,13,14\}} \theta_{10,k,j} x_{10,j}\right)}{1 + \exp\left(\sum_{j \in \{5,9,13,14\}} \theta_{10,k,j} x_{10,j}\right)}, & k \in \{1\}, \\ \frac{1}{1 + \exp\left(\sum_{j \in \{5,9,13,14\}} \theta_{10,k,j} x_{10,j}\right)}, & k \in \{2\}. \end{cases} \quad (39)$$

Table B24. Posterior statistics of the parameters in the predictive model of I_9 .

Parameter	Mean	Standard Deviation
$\theta_{9,1,1}$	23.73	4.36
$\theta_{9,1,2}$	0.02	0.05
$\theta_{9,1,11}$	-2.14	1.01
$\theta_{9,1,12}$	-6.89	1.05
$\theta_{9,2,1}$	25.17	4.26
$\theta_{9,2,2}$	-0.08	0.05
$\theta_{9,2,11}$	-2.08	0.97
$\theta_{9,2,12}$	-5.43	0.96
$\theta_{9,3,1}$	20.46	4.15
$\theta_{9,3,2}$	-0.11	0.05
$\theta_{9,3,11}$	-0.77	0.92
$\theta_{9,3,12}$	-4.09	0.88
$\theta_{9,4,1}$	15.80	4.21
$\theta_{9,4,2}$	-0.10	0.05
$\theta_{9,4,11}$	0.62	0.99
$\theta_{9,4,12}$	-3.71	0.90

Parameter	Mean	Standard Deviation
$\theta_{9,5,1}$	10.72	3.85
$\theta_{9,5,2}$	-0.01	0.04
$\theta_{9,5,11}$	-0.34	0.91
$\theta_{9,5,12}$	-2.57	0.80
$\theta_{9,6,1}$	4.73	3.50
$\theta_{9,6,2}$	-0.09	0.04
$\theta_{9,6,11}$	0.59	0.83
$\theta_{9,6,12}$	-0.56	0.69

Table B25. Codebook of the indicator I_{10} := "Dwelling Ownership."

Category	Codebook	Percentage of Population
Owns the dwelling	1	48.2
Rents the dwelling	2	51.8

Table B26. List of candidate regressors for the predictive model of I_{10} .

Regressor
$x_{10,1} :=$ Constant
$x_{10,2} :=$ Gender of the household head
$x_{10,3} :=$ Age of the household head
$x_{10,4} :=$ Household size
$x_{10,5} :=$ Marital status of the household head
$x_{10,6} :=$ Occupational group of the household head
$x_{10,7} :=$ Education level of the household head
$x_{10,8} :=$ Number of members contributing to household income

Regressor
$x_{10,9} :=$ Road construction project in last five years
$x_{10,10} :=$ Time to the nearest school
$x_{10,11} :=$ Time to the nearest hospital
$x_{10,12} :=$ Time to the nearest food market
$x_{10,13} :=$ Main source of drinking water
$x_{10,14} :=$ Welfare quintile

Table B27 summarizes the posterior statistics of the model parameters. The regressors in the final form of the model are generally noncausal. In evaluating the capabilities of households in the aftermath of a disruption, the ownership status does not change; however, there might be damage (from slight to complete collapse) to the property. This latter possibility can be evaluated by performing structural analysis of individual buildings or more generally, by predicting the level of damage to buildings of certain types, due to a particular hazard, by means of physical loss assessments.

Table B27. Posterior statistics of the parameters in the predictive model of I_{10} .

Parameter	Mean	Standard Deviation
$\theta_{10,5}$	0.93	0.19
$\theta_{10,9}$	-2.37	0.40
$\theta_{10,13}$	-0.13	0.27
$\theta_{10,14}$	0.93	0.22

Capability: “Being Mobile”

Ideally, it is desirable to have an indicator that truly captures the achieved functioning in the capability of “Being Mobile.” For example, the number of travels per day that individuals undertake could be a suitable choice. The capability of “Being Mobile” is related to the availability of paved roads, availability of vehicle for travel, and social norms that may prevent someone from traveling. The number of travels that individuals can make accounts for such factors. In the absence of such an ideal choice, however,

the indicator “Time to the Nearest Food Market” was selected to quantify the achieved functioning. This indicator set the purpose of travel as a generic one that individuals generally may choose to do. The time of travel can capture the availability of the vehicle or paved roads. However, care should be taken in interpreting the results because if the time to the nearest food market being changed, this does not *necessarily* lead to a change in this capability, given that everything else remains the same. For prediction purposes, the network analysis of infrastructure systems is used to obtain the likely outcome in the aftermath of a disruption.

Capability: “Being Educated”

Disruptive events can adversely impact the capability of “Being Educated” by causing damage to the building or stopping the building from functioning due to, for example, loss of power. The influence of such impacts generally becomes a matter of time and how long they last. Not being able to go to school for a week or a month might not be too critical. However, not being able to educate in general is a big issue. Though this capability might not be significantly impacted by a disruptive event, when quantifying the overall capabilities of individuals, it can make a difference to account for it.

To quantify the achieved functioning in this capability, two indicators were used, which are “Time to the Nearest School” and “Frequency of Problems Paying School Fees.” To predict the value of the first indicator in the aftermath of a disruption, the network analysis of infrastructure systems is used. Regarding the second indicator, Equation (3) was used to develop a probabilistic predictive model.

Table B28 shows the codebook of the indicator “Frequency of Problems Paying School Fees” along with the percentage of the considered households within each category. Table B29 lists the set of all candidate regressors considered for developing the predictive model. After eliminating the statistically insignificant terms, the final form of the model is shown as Equation (40):

$$\mathbf{P}[I_{13}(\mathbf{x}_{13}, \Theta_{13}) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{1,6,11\}} \theta_{13,k,j} x_{13,j}\right)}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{1,6,11\}} \theta_{13,k,j} x_{13,j}\right)}, & k \in \{1, 2, 3\}, \\ \frac{1}{1 + \sum_{k=1}^3 \exp\left(\sum_{j \in \{1,6,11\}} \theta_{13,k,j} x_{13,j}\right)}, & k \in \{4\}. \end{cases} \quad (40)$$

Table B28. Codebook of the indicator I_{13} := “Frequency of Problems Paying School Fees.

Category	Codebook	Percentage of Population
Never	1	75.2
Seldom	2	10.6
Sometimes	3	8.7
Often/Always	4	5.6

Table B29. List of candidate regressors for the predictive model of I_{13} .

Regressor
$x_{13,1} :=$ Constant
$x_{13,2} :=$ Age of the household head
$x_{13,3} :=$ Household size
$x_{13,4} :=$ Marital status of the household head
$x_{13,5} :=$ Occupational group of the household head
$x_{13,6} :=$ Education level of the household head
$x_{13,7} :=$ Number of members contributing to household income
$x_{13,8} :=$ Road construction project in last five years
$x_{13,9} :=$ Time to the nearest school
$x_{13,10} :=$ Time to the nearest food market

Regressor
$x_{13,11} :=$ Main source of drinking water
$x_{13,12} :=$ Welfare quintile
$x_{13,13} :=$ Dwelling ownership

Table B30 summarizes the estimate posterior statistics of the model parameters. As discussed earlier, the capability in general, and the category of the indicator in particular, might not change over a short-term period. However, it is still important to account for such capability in assessing the well-being of individuals. Hence, the regressors are of noncausal type, and they show a general relation between the category of the indicator and the regressors. Specifically, the education of the household head is intuitively connected to the category of the indicator. However, the relation between the source of drinking water and the category of indicator is less tangible, and it might refer to social status of the household and whether or not they can afford the school fees.

Table B30. Posterior statistics of the parameters in the predictive model of I_{13} .

Parameter	Mean	Standard Deviation
$\theta_{13,1,1}$	6.10	1.89
$\theta_{13,1,6}$	-0.72	0.21
$\theta_{13,1,11}$	-0.88	0.82
$\theta_{13,2,1}$	-1.44	2.30
$\theta_{13,2,6}$	-0.22	0.23
$\theta_{13,2,11}$	1.36	0.94
$\theta_{13,3,1}$	-4.80	2.64
$\theta_{13,3,6}$	0.04	0.26
$\theta_{13,3,11}$	2.32	1.01

Capability: “Having Access to Medical Services”

A disruptive event may hinder the ability to access hospitals or make medical services unavailable. When a disruptive event endangers the life of individuals or causes injuries, the capability of “Having Access To Medical

Services” becomes of utmost significance. To quantify the achieved functioning in this capability, two indicators were considered: “Time to the Nearest Hospital” and “Frequency of Problems Paying for Healthcare.” The selected indicators are supposed to collectively capture the ease to access to medical services. Access to medical services in general can be influenced by proximity of medical services, availability of resources such as the doctor-to-patient ratio, facilities of the hospitals and healthcare centers, and the costs. Regarding the first indicator, the infrastructure network analysis was used to predict the likely value of the indicator in the aftermath of a disruption. This indicator plays a major role in evaluating the capabilities of individuals during any emergencies that arise in the aftermath of a disruption. In contrast, the second indicator is more pertinent for evaluating the level access to medical services during the stable condition of the society. To predict the likely category of this indicator, Equation (3) was used to develop a probabilistic predictive model.

Table B31 shows the codebook and the percentage of the considered household in each category. Table B32 lists the set of all candidate regressors considered for developing the predictive model. As before, the stepwise deletion process was used to eliminate the statistically insignificant terms. The final form of the model after the deletion process is shown in Equation (41):

$$\mathbf{P}[I_{15}(\mathbf{x}_{15}, \Theta_{15}) = k] = \begin{cases} \frac{\exp\left(\sum_{j \in \{11,13\}} \theta_{15,k,j} x_{15,j}\right)}{1 + \sum_{k=1}^4 \exp\left(\sum_{j \in \{11,13\}} \theta_{15,k,j} x_{15,j}\right)}, & k \in \{1, \dots, 4\}, \\ \frac{1}{1 + \sum_{k=1}^4 \exp\left(\sum_{j \in \{11,13\}} \theta_{15,k,j} x_{15,j}\right)}, & k \in \{5\}. \end{cases} \quad (41)$$

Table B31. Codebook of the indicator I_{15} := “Frequency of Problems Paying for Healthcare.”

Category	Codebook	Percentage of Population
Never	1	35.2
Seldom	2	2.5
Sometimes	3	57.4

Category	Codebook	Percentage of Population
Often	4	3.1
Always	5	1.9

Table B32. List of candidate regressors for the predictive model of I_{15} .

Regressor
$x_{15,1} :=$ Constant
$x_{15,2} :=$ Gender of the household head
$x_{15,3} :=$ Age of the household head
$x_{15,4} :=$ Household size
$x_{15,5} :=$ Occupational group of the household head
$x_{15,6} :=$ Education level of the household head
$x_{15,7} :=$ Number of members contributing to household income
$x_{15,8} :=$ Road construction project in last five years
$x_{15,9} :=$ Time to the nearest school
$x_{15,10} :=$ Time to the nearest hospital
$x_{15,11} :=$ Time to the nearest food market
$x_{15,12} :=$ Main source of drinking water
$x_{15,13} :=$ Welfare quintile

Table B33 summarizes the estimated posterior statistics of the model parameters. There are two regressors that remain in the model. The regressor $x_{15,11}$ is of noncausal type, and the regressor $x_{15,13}$ is causal (that explains whether a household can afford the expenses of medical services).

Table B33. Posterior statistics of the parameters in the predictive model of I_{15} .

Parameter	Mean	Standard Deviation
$\theta_{15,1,11}$	-0.60	0.68
$\theta_{15,1,13}$	1.68	0.53
$\theta_{15,2,11}$	0.19	0.71
$\theta_{15,2,13}$	0.23	0.61
$\theta_{15,3,11}$	1.07	0.61
$\theta_{15,3,13}$	0.91	0.51
$\theta_{15,4,11}$	-0.12	0.82
$\theta_{15,4,13}$	0.37	0.64

Capability: “Being Socially Connected”

The capability of “Being Socially Connected” refers to the aspect of well-being that humans, as social creatures, live together, not only because living together is instrumentally beneficial, but also because humans have a sense of belonging to or being affiliated with a group, association, community, or region. From the instrumental perspective, “Being Socially Connected” acts more like a mean to achieve a higher level of acceptance; hence, it can be interpreted more like a regressor than a capability. However, from the capability point of view, it is an independent aspect of well-being which is intrinsically important. To quantify the achieved functioning in this capability, the binary indicator “Can Household Depend on Religious Association during Difficult Period?” was selected.

Table B34 shows the codebook of the indicator, along with the percentage of the considered individuals in each category. Table B35 lists the set of candidate regressors considered for developing the predictive model. As usual, the stepwise deletion process is used to eliminate the statistically insignificant terms and arrive at a parsimonious form of the model, represented as Equation (42):

$$\mathbf{P}\left[I_{16}(\mathbf{x}_{16}, \Theta_{16}) = k\right] = \begin{cases} \frac{\exp\left(\sum_{j \in \{1, 11, 13\}} \theta_{16,k,j} x_{16,j}\right)}{1 + \exp\left(\sum_{j \in \{1, 11, 13\}} \theta_{16,k,j} x_{16,j}\right)}, & k \in \{1\}, \\ \frac{1}{1 + \exp\left(\sum_{j \in \{1, 11, 13\}} \theta_{16,k,j} x_{16,j}\right)}, & k \in \{2\}. \end{cases} \quad (42)$$

Table B34. Codebook of the indicator I_{16} := “Can Household Depend on Religious Association during Difficult Period?”

Category	Codebook	Percentage of Population
Yes	1	53.5
No	2	46.5

Table B35. List of candidate regressors for the predictive model of I_{16} .

Regressor
$x_{16,1}$:= Constant
$x_{16,2}$:= Sex
$x_{16,3}$:= Age
$x_{16,4}$:= Marital status
$x_{16,5}$:= Radio, frequency of use
$x_{16,6}$:= Daily newspaper, frequency of use
$x_{16,7}$:= Highest grade completed
$x_{16,8}$:= Standard of living relative to others in the community
$x_{16,9}$:= Household financial situation
$x_{16,10}$:= Time to the nearest school
$x_{16,11}$:= Time to the nearest hospital
$x_{16,12}$:= Time to the nearest food market

Regressor
$x_{16,13} :=$ Does household belong to a family association
$x_{16,14} :=$ Can read a simple letter in what Nigerian language

Table B36 summarizes the estimate posterior statistics of the model parameters. The regressors in the final form of the model are noncausal; thus, as before, it would be suggested not to change the category of the indicator for the purpose of predicting the capability of households in the immediate aftermath of a disruption.

Table B36. Posterior statistics of the parameters in the predictive model of I_{16} .

Parameter	Mean	Standard Deviation
$\theta_{16,1,1}$	12.11	1.43
$\theta_{16,1,11}$	-1.44	0.30
$\theta_{16,1,13}$	-6.95	0.77

Appendix C: Figures

Figures C1-C10 show the relation between the values/categories of the indicators and their states. In general, each capability indicator can have three states: (1) the acceptable state (green), (2) the tolerable state (yellow), and (3) the intolerable state (red). However, note that not all the indicators necessarily have the three states. This is because either the number of possible categories/values is less than 3 like the indicator "source of electricity" or the nature of the indicator is such that not all the three states are realizable, like the indicator "number of household durables."

Figure C1. The states of the indicators quantifying the capability of “Meeting the Physiological Needs” (University of Illinois).

Main source of drinking water	Pipe borne, treated	Vendor, truck	Others
Frequency of problems with supply of drinking water	No	Dry season	Frequently
Frequency of problems satisfying food needs	Never	Seldom	Sometimes
			Often

Figure C2. The states of the indicator quantifying the capability of “Being Physically Safe” (University of Illinois).

Do members feel safe walking on street at night?	Very safe	Somewhat safe	Not too safe
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Figure C3. The states of the indicator quantifying the capability of “Being Sheltered” (University of Illinois).

Frequency of problems paying house rent	Never	Seldom	Sometimes	Often
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Figure C4. The states of the indicator quantifying the capability of “Having Access to Energy” (University of Illinois).

Source of electricity	NEPA	None
Number of hours without electricity in the past 24 hours	0-6 hours	6-12 hours
		>12 hours

Figure C5. The states of the indicator quantifying the capability of “Earning Income” (University of Illinois).

Household financial situation	Fairly rich	Moderate	Poor	Very poor
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Figure C6. The states of the indicators quantifying the capability of “Owning Property” (University of Illinois).

Number of household durables	2-6	0-1
Dwelling ownership	Owns	Rents

Figure C7. The states of the indicator quantifying the capability of “Being Mobile” (University of Illinois).

Time to the nearest food market	0-14 min	15-29 min	30-44 min	45-59 min	60+ min
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Figure C8. The states of the indicators quantifying the capability of “Being Educated” (University of Illinois).

Time to the nearest school	0-14 min	15-29 min	30-44 min	45-59 min	60+ min
Frequency of problems paying school fees	Never	Seldom	Sometimes	Sometimes	Often

Figure C9. The states of the indicators quantifying the capability of “Having Access to Medical Services” (University of Illinois).

Time to the nearest hospital	0-14 min	15-29 min	30-44 min	45-59 min	60+ min
Frequency of problems paying for healthcare	Never	Seldom	Sometimes	Often	Always

Figure C10. The states of the indicators quantifying the capability of “Being Socially Connected” (University of Illinois).

Can household depend on religious association during difficult period?	Yes	No
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Figures C11-C20 show the predicted states of the capability indicators of the households in the study region, before and after the occurrence of a disruptive scenario. Visual inspection of the plots reveals which capability indicators have urgent needs to be improved and also in what regions people suffer the most and need to be prioritized. In addition, there is an overall “capability state” map in Figure C21 that gives an aggregate picture of the well-being state. Comparing the maps before and after the disruption explains in what regions people suffer more consequences from the disruption.

Figure C11. The spatial distribution of well-being in terms of the averaged capability of “Meeting the Physiological Needs,” before (left) and after (right) the disruption (ERDC-CERL).

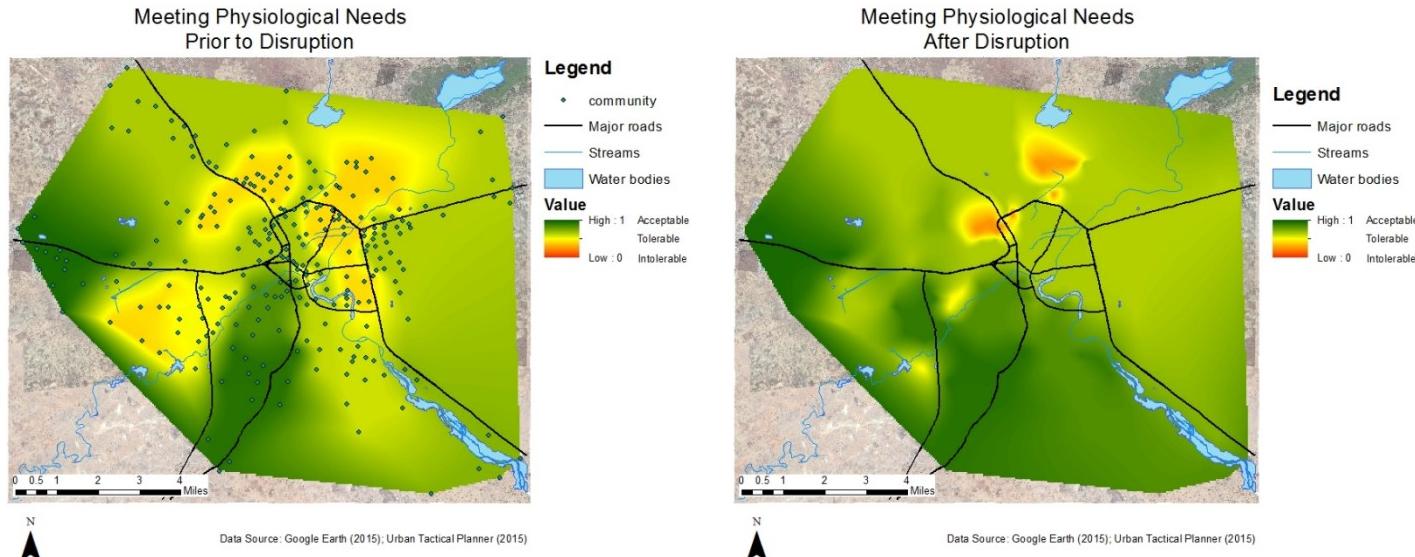


Figure C12. The spatial distribution of well-being in terms of the averaged capability of “Being Physically Safe,” before (left) and after (right) the disruption (ERDC-CERL).

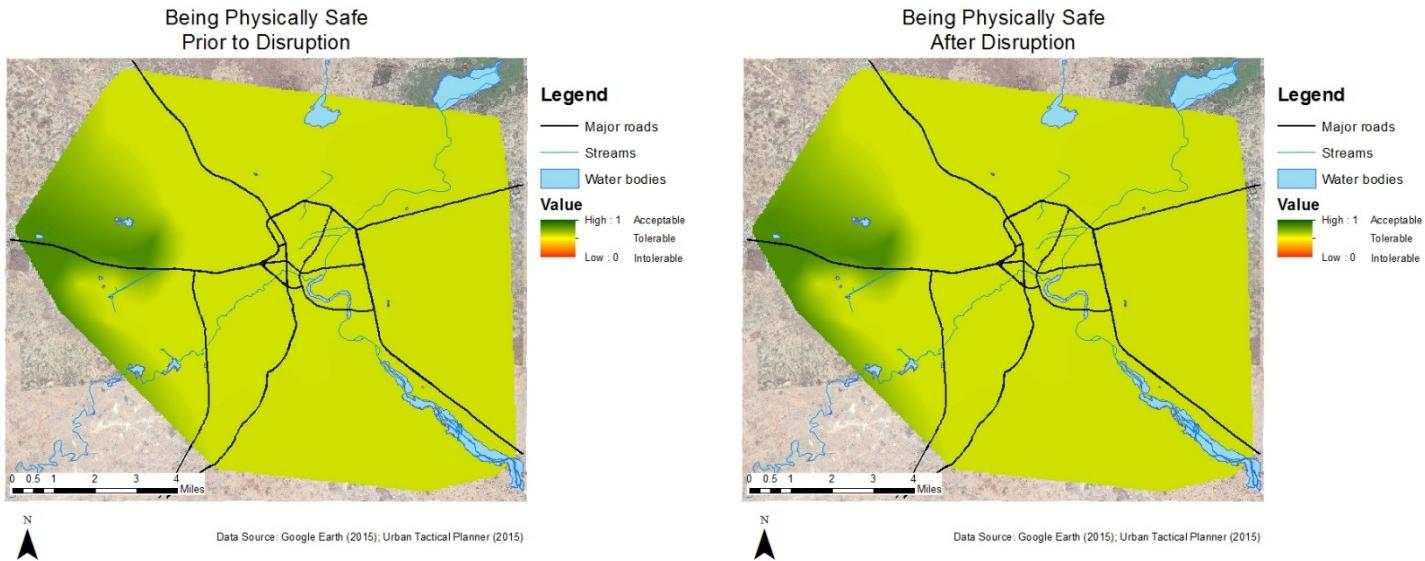


Figure C13. The spatial distribution of well-being in terms of the averaged capability of “Being Sheltered,” before (left) and after (right) the disruption (ERDC-CERL).

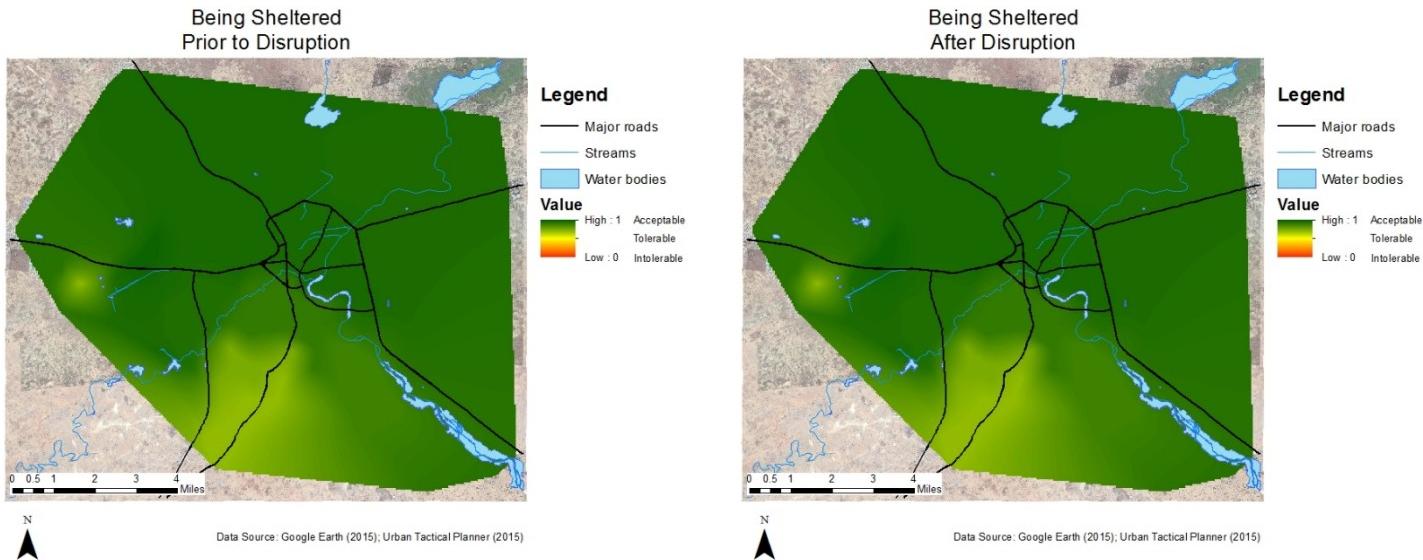


Figure C14. The spatial distribution of well-being in terms of the averaged capability of "Having Access to Energy," before (left) and after (right) the disruption (ERDC-CERL).

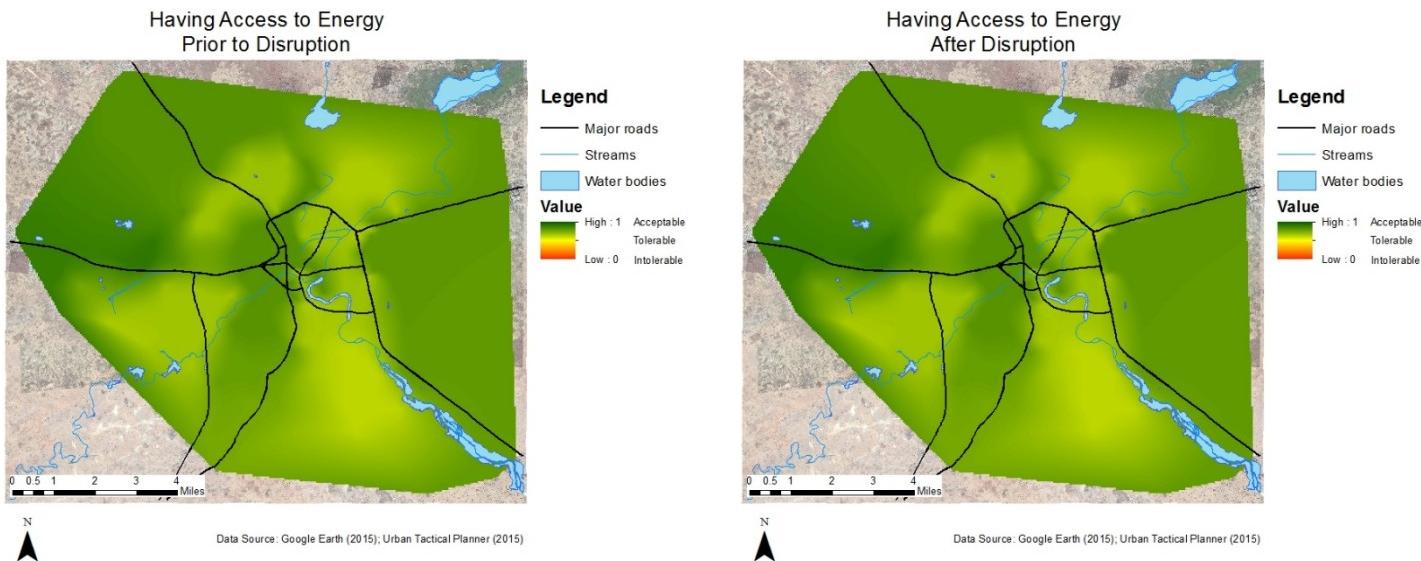


Figure C15. The spatial distribution of well-being in terms of the averaged capability of "Earning Income," before (left) and after (right) the disruption (ERDC-CERL).

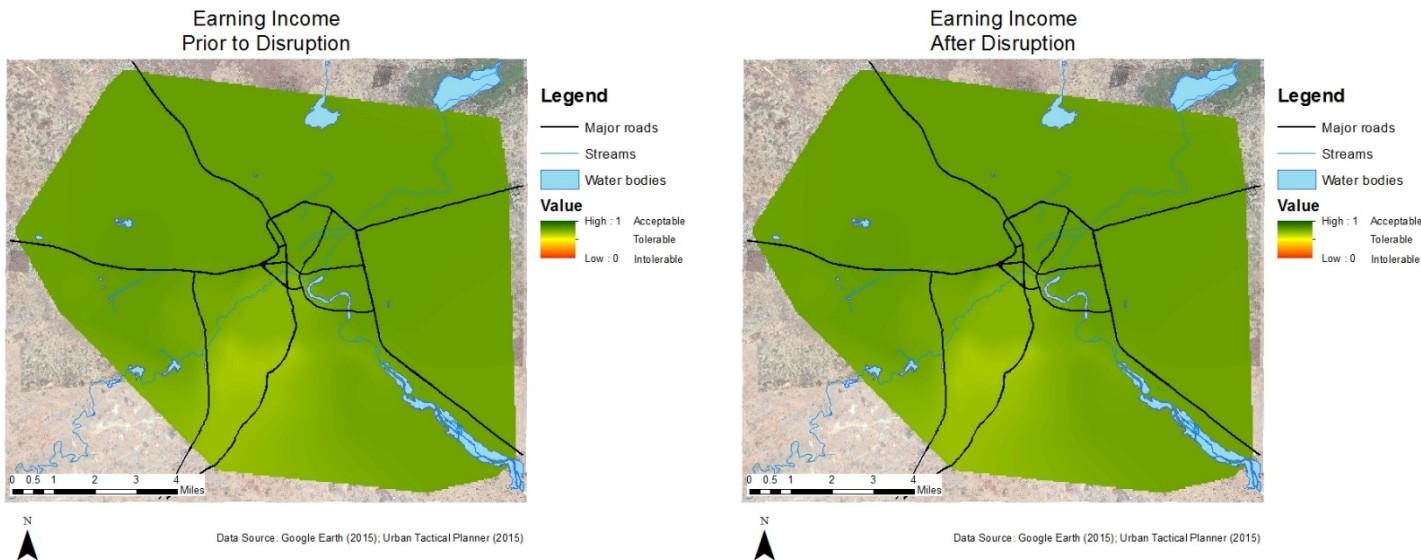


Figure C16. The spatial distribution of well-being in terms of the averaged capability of “Owning Property,” before (left) and after (right) the disruption (ERDC-CERL).

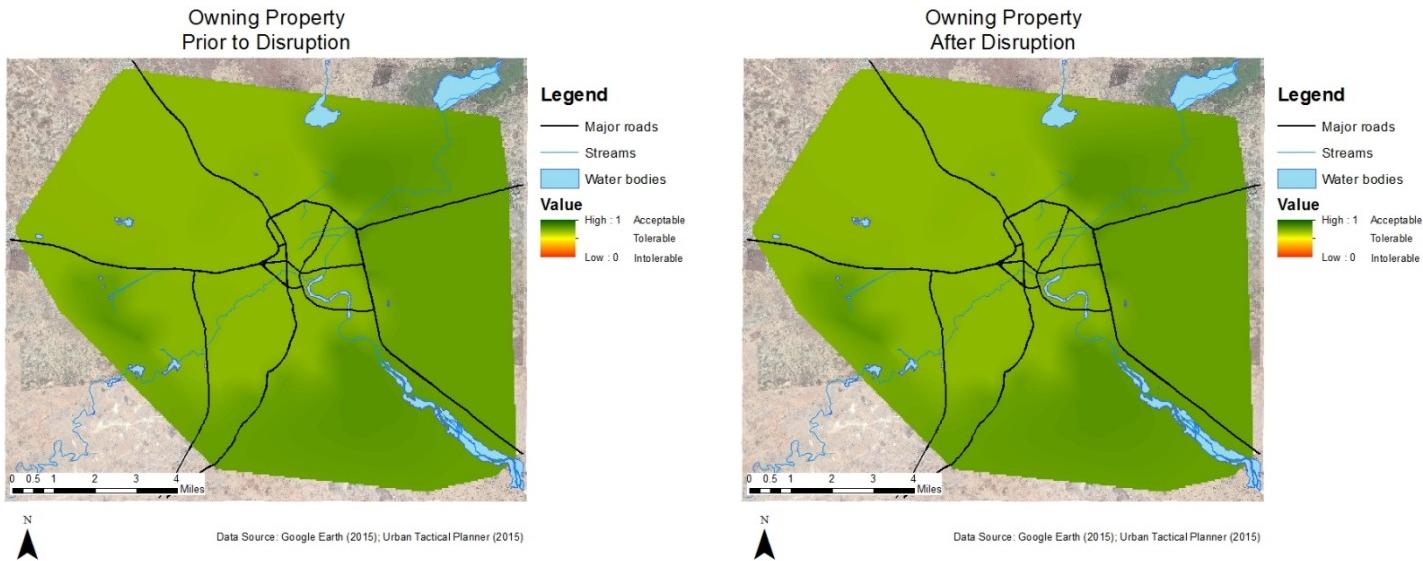


Figure C17. The spatial distribution of well-being in terms of the averaged capability of “Being Mobile,” before (left) and after (right) the disruption (ERDC-CERL).

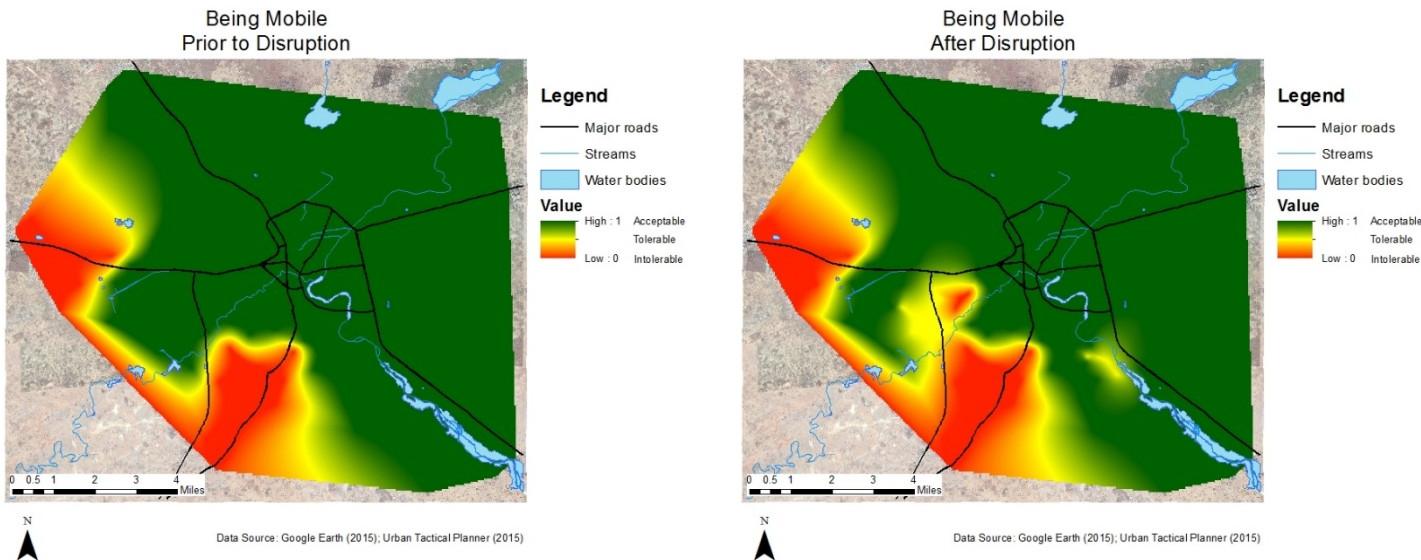


Figure C18. The spatial distribution of well-being in terms of the averaged capability of “Being Educated,” before (left) and after (right) the disruption (ERDC-CERL).

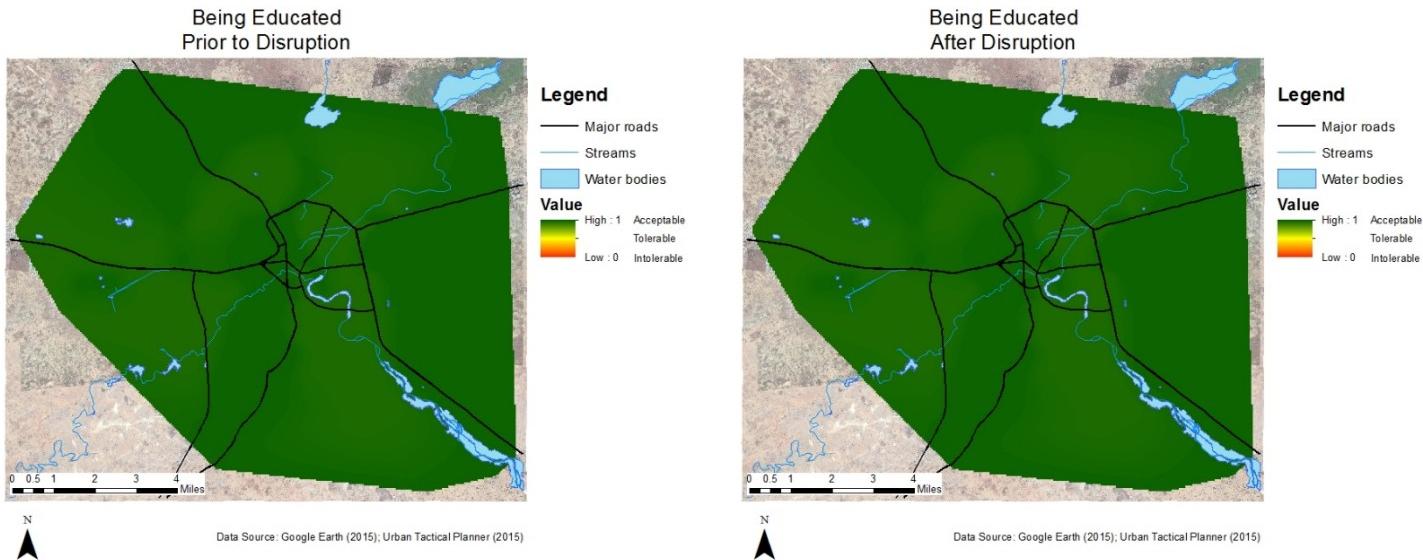


Figure C19. The spatial distribution of well-being in terms of the averaged capability of “Having Access to Medical Services,” before (left) and after (right) the disruption (ERDC-CERL).

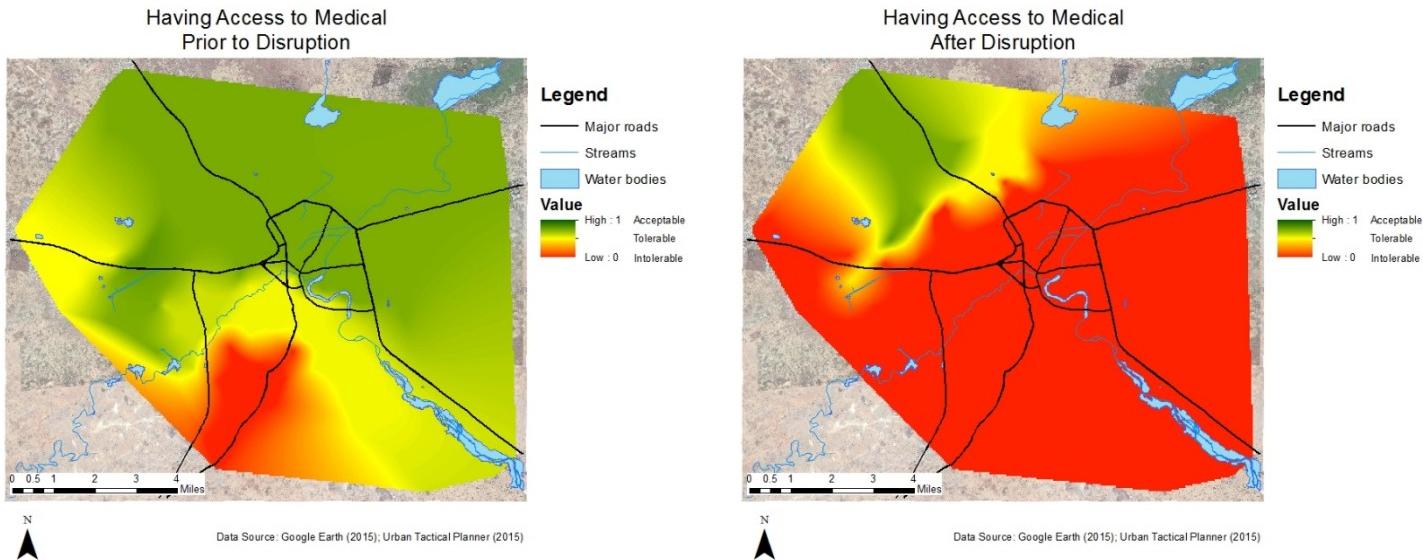


Figure C20. The spatial distribution of well-being in terms of the averaged capability of “Being Socially Connected,” before (left) and after (right) the disruption (ERDC-CERL).

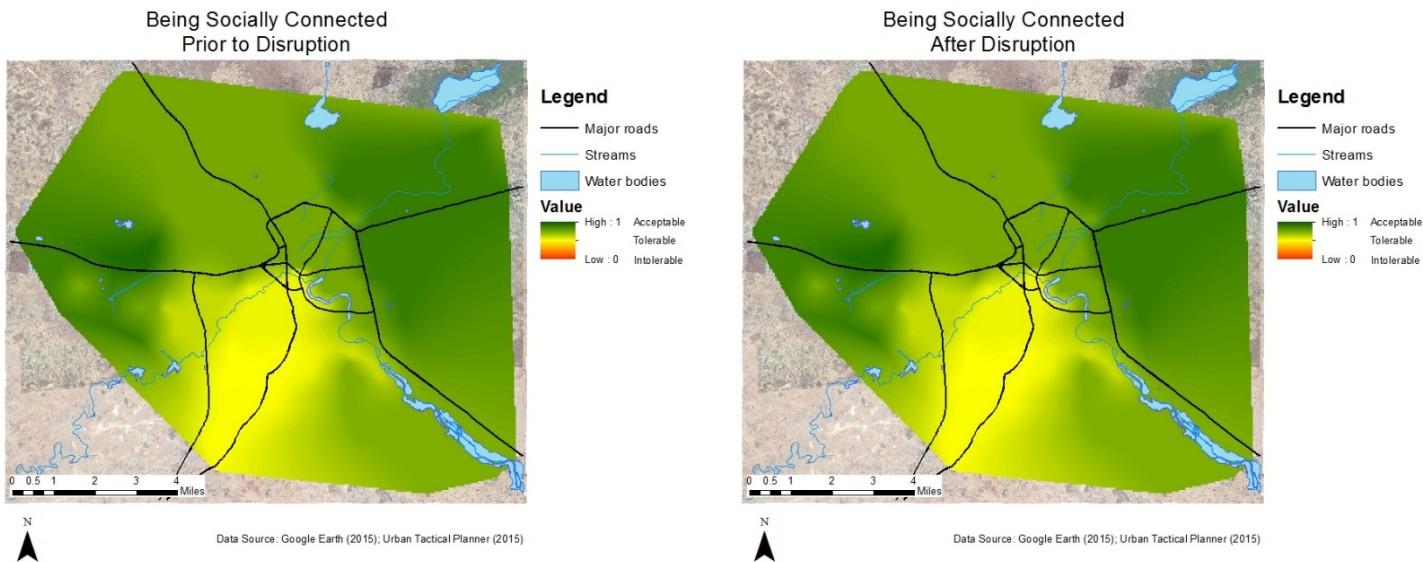
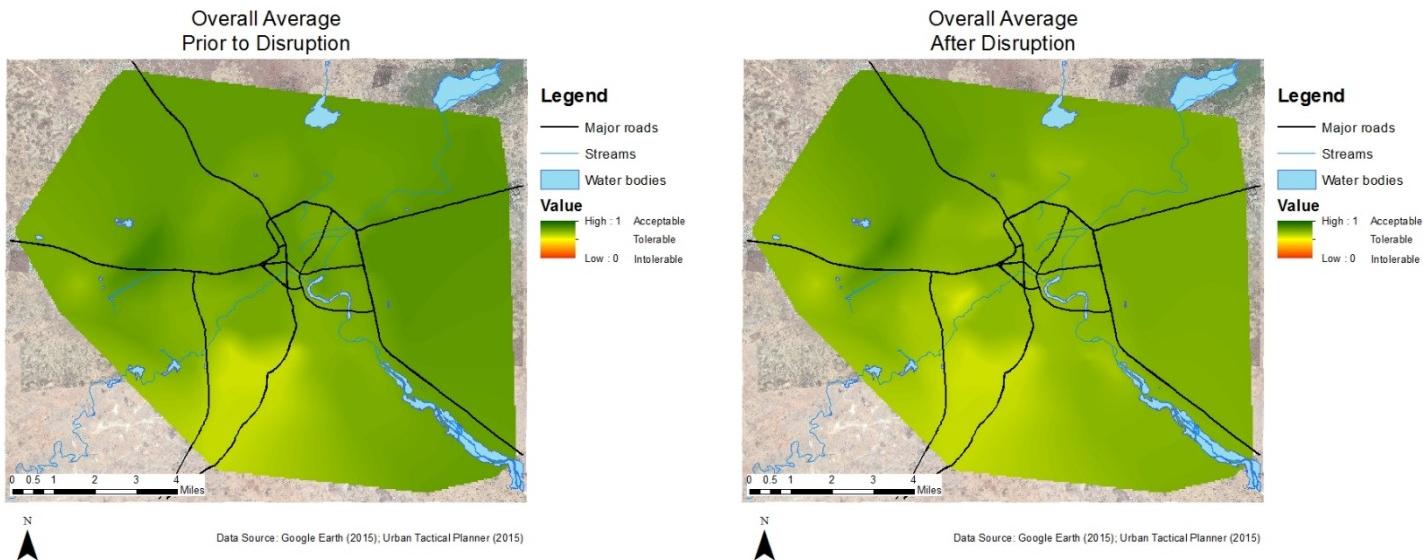


Figure C21. The spatial distribution of well-being in terms of the averaged overall capability, before (left) and after (right) the disruption (ERDC-CERL).



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14. ABSTRACT U.S. Army doctrine requires that commanders understand, visualize, and describe the infrastructure component of the Joint Operating Environment to accomplish the Army's missions of protecting, restoring, and developing infrastructure. The functionality of modern cities relies heavily on interdependent infrastructure systems such as those for water, power, and transportation. Disruptions often propagate within and across physical infrastructure net-works and result in catastrophic consequences. The reaction of communities to disasters may further transfer and aggravate the burden and facilitate cascading secondary disruptions. Hence, a holistic analysis framework that integrates infrastructure interdependencies and community behaviors is needed to evaluate vulnerability to disruptions and to assess the impact of a disaster. The research for Human-Infrastructure System Assessment (HISA) for Military Operations adopts the Capability Approach (CA) to measure and predict the impact of potential infrastructural interdictions on the City of Maiduguri, Borno State, Nigeria. With the CA, 10 capabilities are identified to describe the well-being levels of Maiduguri. To quantify these 10 capabilities, 16 indicators were chosen to represent them. These indicator justifications provide the rationale for choosing the indicators for the corresponding capabilities and predictive modeling. Developing probabilistic predictive models of the indicators (or their indices) allows analysis of social well-being in relationship to cascading infrastructure failure.					
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